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# Demand-Side Industrial Policy and Foreign Direct Investment: Evidence from Electric Vehicle Battery Industry

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**Abstract**

This paper studies how demand-side industrial policy affects domestic production and foreign direct investment (FDI). I use the U.S. Inflation Reduction Act (IRA) to quantify the effects of consumer subsidies and domestic content requirements on production, employment, consumption, and supply-chain structure in the electric vehicle (EV) industry. I develop a multi-sector general equilibrium trade model with heterogeneous consumers and producers, multi-stage production, and taxation. The quantitative results show that the IRA increases domestic output and employment in the EV battery industry and attracts FDI, but at the cost of lower aggregate EV sales. The magnitude of this trade-off depends on the stringency of the domestic content requirement: looser thresholds generate larger employment and FDI gains but amplify the decline in overall EV adoption. Holding fixed the induced battery-industry FDI, the IRA industrial policy delivers larger employment gains than import tariff-based policies.

**Keywords:** *Industrial Policy, Consumer Heterogeneity, Foreign Direct Investment, Electric Vehicles, Electric Vehicle Batteries, Trade Policy*

**JEL Codes:** F13, L52, L62, Q48

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# 1 Introduction

The world is witnessing a revival of industrial policy, with a growing shift toward demand-side instruments such as consumer subsidies.[1] Unlike traditional approaches centered on producer subsidies or trade protection, these policies are often designed to shape consumer demand in response to new objectives related to climate change, supply chain resilience, and strategic competition with geopolitical rivals. Yet our understanding of their economic implications – particularly for production structure, employment, and multinational activity – remains incomplete.

This paper studies how demand-side industrial policy affects domestic production and foreign direct investment (FDI), focusing on the U.S. Inflation Reduction Act (IRA). The policy offers means-tested subsidies for electric vehicles (EVs) purchases, conditional on domestic content requirements. I show that the IRA increases domestic production and employment in the battery industry, with larger FDI inflow, but reduces overall EV sales. This trade-off arises from heterogeneous consumer responses: eligible consumers drive gains in the battery industry, while ineligible ones contribute to lower EV sales. The magnitude of the trade-off varies with the domestic content requirement – looser thresholds yield larger employment and FDI gains but deepen the decline in EV adoption. Conditional on comparable FDI, the IRA generates greater employment gains than an equivalent import tariff policy.

I develop a two-country, multi-sector general equilibrium model of international trade featuring heterogeneous consumers and producers, multi-stage production, and taxation. Consumers differ in their income levels, which determine their propensity to purchase EVs relative to gasoline vehicles (GVs). EV producers face two problems: (*i*) they choose their target consumer base; (*ii*) they decide the extent to which batteries are sourced domestically versus imported. Battery producers, in turn, determine whether to serve foreign markets through export or FDI.

In this environment, the introduction of means-tested subsidies and domestic content requirements generates three key effects. First, these policies can expand the consumer base by encouraging purchases among eligible individuals, thereby stimulating demand in the domestic battery industry. However, they also raise production costs, leading to higher vehicle prices. Therefore,

[1] See, for example, Aiginger and Rodrik (2020).

purchases by ineligible consumers may decline, offsetting potential gains from eligible buyers. The aggregate impact of these opposing forces depends on their relative strength and can only be evaluated through the lens of a quantitative model.

I calibrate the model to the United States as the home country and to an aggregate of 13 developed countries representing the foreign economy, using data for 2019. The model replicates key features of the U.S. and global EV and battery market. Using the calibrated model, I quantify the effects of the IRA. The subsidy rate is set at 25%, corresponding to the calibrated share of the average EV price covered by the subsidy and the domestic content requirement starts at 50%, the minimum threshold specified by the IRA. The results show that domestic production increases by 132% and the employment by 136% with the share of foreign producers relocating to the United States rising from 7.1% to 14.1%. In contrast, aggregate EV sales decline by 2.25%.

Then, I conduct two counterfactual experiments. The first examines comparative statics along the IRA's phased policy schedule, using 50% as the benchmark and gradually increasing the domestic content threshold to 90%. The results show that gains in battery industry diminish while the losses in overall EV sales moderate as the threshold tightens. At a 90% threshold, domestic production and employment gains fall to 40% and 64%, respectively, and the FDI share declines to 6.7%, while the decline in EV sales attenuates to -1.7%. The second experiment compares the IRA with an import-tariff policy. At a comparable FDI share of 14%, the tariff policy yields employment gains in the battery industry that are 36 percentage points lower than under the IRA. Achieving the same level of employment would require a tariff rate of 100%.

This paper is related to several strands of literature. First, it contributes to the emerging literature of industrial policy and trade policy (Aiginger and Rodrik, 2020; Criscuolo et al., 2022a,b; Juhász et al., 2023; Juhász and Lane, 2024; Evenett et al., 2024; Bown, 2024). These studies introduce new characteristics of recent industrial policies which differ from earlier ones in their background, objectives, and policy design. Several papers evaluate such policies in strategic industries that promote innovation and the diffusion of green technologies and products (Allcott and Kane, 2024; Head et al., 2024; Ju et al., 2024; **?**; Goldberg et al., 2024; Slowik et al., 2023). However, there is still no study assessing how demand-side instrument can contribute to transformative industrial change, despite their widespread use across countries. This paper provides the first quantitative analysis to fill this gap.

Second, this paper relates to the growing literature on EV adoption (Gillingham et al., 2023; Springel, 2021; Li et al., 2022; Muehlegger and Rapson, 2023; Barwick et al., 2024). These studies examine both financial and non-financial factors, such as charging infrastructure and vehicle attributes that influence consumers' uptake of EVs, but they pay less attention to consumer heterogeneity in adoption. A number of papers (Muehlegger and Rapson, 2022; Linn and Shen, 2024; Borenstein and Davis, 2016) highlight the distributional effect of EV purchase subsidies, emphasizing the role of household income. Consistent with this literature, I employ non-homothetic preferences for EVs combined with income inequality among households to examine heterogeneous consumption responses. This framework captures how the composition of EV demand across income groups changes with the subsidy, which is a critical channel for understanding how the demand-side incentives propagate along the supply chain.

Lastly, this paper relates to the literature on the determinants of FDI. A prominent view on the horizontal FDI emphasizes the proximity–to-concentration trade-off (Markusen, 1984). Beyond trade costs and scale economies that shape this trade-off, this paper highlights the role of market size. Related literature includes Brainard (1997), Carr et al. (2001), Markusen (2002), Markusen and Maskus (2002), Helpman et al. (2004), Yeaple (2009), Fajgelbaum et al. (2015). Based on these studies, I develop a two-country model of heterogeneous firms (Helpman et al., 2004) in which firms can either export or engage in FDI. By allowing market size to differ across modes rather than between countries, the model generates a mechanism through which an expansion in domestic demand attracts input firms' FDI.

In the remainder of the paper, section 2 provides background on the U.S. IRA policy together with EV and battery markets. Section 3 introduces theoretical framework and policy intervention. In section 5 and 6, the model is calibrated, quantitative results are presented and the paper concludes.

# 2 Background

In this section, I provide background information on the EV market and the battery industry in both the United States and the global context, as well as on the EV tax credit policy under the U.S. Inflation Reduction Act.

## 2.1 Data

For the analysis of the EV market, I use two datasets: $(i)$ the IEA Database (IEA, 2025), and $(ii)$ State EV Registration Data for the United States by Atlas EV Hub. Both datasets are publicly available. The IEA Database reports both EV sales in 55 countries and EV battery demand by region from 2010 to 2024. I also use data from the IEA Global EV Outlook published annually in its website.

In addition, the State EV Registration Data by Atlas EV Hub reports EV make, model, and year by region (zip code or county), registration date, and vehicle attributes for 14 U.S. states[2] from 2010 to 2025. I construct a county-level sample of light-duty battery EVs registered quarterly from 2017 to 2021. I also restrict observations so that the difference between the registration year and the model year is less than one year, allowing the sample to proxy EV purchases. I then compute county-level EV prices as weighted averages, using MSRPs that I hand-collected at the make–model–year level[3].

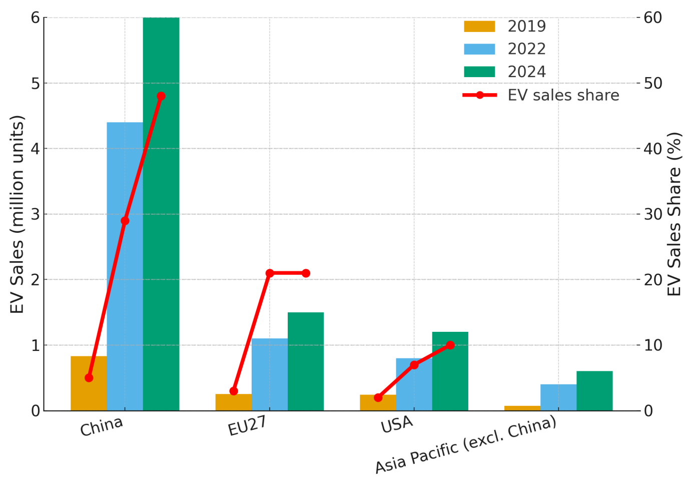
Unlike EVs, there is no publicly available county-level registration data for GVs. However, the Department of Energy releases annual state-level vehicle sales by fuel type, and Kelley Blue Book press releases provide U.S. monthly average auto prices. I apportion these to counties using each county's share of the state population and its per-capita income relative to the national level, and then combine them with the EV data. The population and income data are from the Census and the Bureau of Economic Analysis (BEA). Lastly, for aggregate consumption and controls, I use consumer expenditure and price index data from both BEA and BLS. Other data sources are reported below.

[2] Colorado, Connecticut, Maine, Minnesota, Montana, New Jersey, New Mexico, New York, North Carolina, Oregon, Tennessee, Texas, Vermont, and Virginia

[3] MSRP sources: InsideEVs, Kelley Blue Book, and press releases from each EV brand.

## 2.2 U.S. Electric Vehicle Market

**EV Adoption** Global electric vehicle (EV) sales have surged in recent years. According to the International Energy Agency (IEA, 2025), the global sales share of battery EVs rose from 3% in 2019 to 15% in 2022 and reached 22% in 2024. Among the countries contributing most to this growth is China. As shown in Figure 1, China is both the largest and fastest-growing market for EVs, with battery EVs accounting for 48% of total vehicle sales in 2024. The European Union (EU) and the United States have also experienced steady increases in EV adoption, but their total sales volumes remain only about 23% and 19% of China's, respectively. While the U.S. sold slightly fewer EVs than the EU, its sales share is considerably lower—21% in the EU compared to just 10% in the U.S.



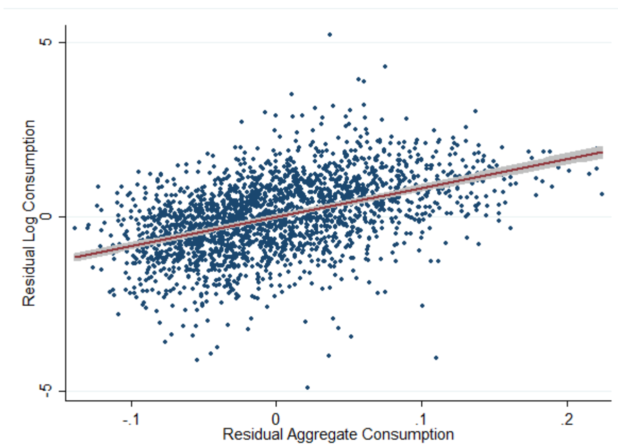

*Notes:* This figure shows the sales of electric vehicles both in units (millions) and percentage in each region from 2019 to 2024. Regions include China, 27 countries in the European Union, United States and countries in Asia Pacific regions excluding China. *Data source: Global Electric Vehicle Outlook 2025*

Figure 1: Electric Vehicle Sales by Region, 2019-2024

There are many reasons for the slow adoption of EVs in the US such as limited charging infrastructure, ineffective policy design, and lack of awareness for new technologies. However, one of the most persistent barriers remains the high purchase price of EVs relative to gasoline vehicles (GVs). A 2023 survey conducted by the European Commission identified the high price of EVs as the primary factor discouraging potential buyers (Vanhaverbeke et al., 2023). In the United States, the average price of EVs was about 50% higher than the overall vehicle average in 2019. Although this price gap narrowed to 15% in 2024, EVs remain more expensive than conventional vehicles.

The trend of higher EV prices in the U.S. may be attributed to the market's orientation toward premium, higher-end models. IEA (2025) reports that the share of EVs sold at less expensive price than comparable conventional vehicles was only 4% in 2021 and 17% in 2024 in the U.S., whereas, in China these shares reached 51% and 65%, respectively. This contrast suggests that the U.S. EV market remains a premium segment, rather than an affordable segment.

Another characteristics of the EV market aligns with its premium orientation is distinct purchasing patterns across income levels. Figure 2 illustrates this relationship by plotting a relative Engel curve of EV-to-GV consumption in the U.S., using county-level registration data from EV Hub. Specifically, the log of residual real EV-to-GV consumption is regressed on the log of residual aggregate real consumption over the period 2019 to 2022. The residuals are obtained from OLS regression with state fixed effects and county-level controls.[4] The figure reveals a clear positive relationship between consumer income and EV adoption: the share of EV purchases relative to GVs increases with income, confirming that EV demand is highly income-elastic. Also, the upward trend does not fade at higher income levels, indicating that the positive relationship between income and EV purchases persists throughout the income distribution. This observation provides the foundation for the theoretical framework employing non-homothetic CES preferences in Section 3.




*Notes:* This figure illustrates partial correlation between relative real electric vehicle (EV) consumption and aggregate real consumption. Using U.S. county-level data from 2019-2022, the figure plots the residual (log) share of real EV consumption relative to gasoline vehicles on the y-axis and residual (log) real income on the x-axis, after partialling out state fixed effects and country-level controls. The positive relationship indicates that the relative consumption of EVs increases with income.

Figure 2: Partial Correlations of electric vehicle and aggregate real consumption

**Electric Vehicle Production** The majority of EV models sold globally are assembled domesti-

[4]Controls include county-level metro-status, average age, sex and education level of the population.

cally. According to the IEA Global EV Outlook 2023, more than 75% of global EV sales originate from domestically produced models rather than imports[5]. This pattern also holds for the U.S. market. Horowitz et al. (2021) reports that 95% and 90% of EVs sold in the U.S. during 2018-2019 were assembled domestically, primarily consisting of the Tesla Model 3, Model X, Model S, Chevrolet Bolt EV and Nissan LEAF. This evidence supports the theoretical assumption that the EV industry is non-tradable in section 3.

### 2.3 Battery Industry

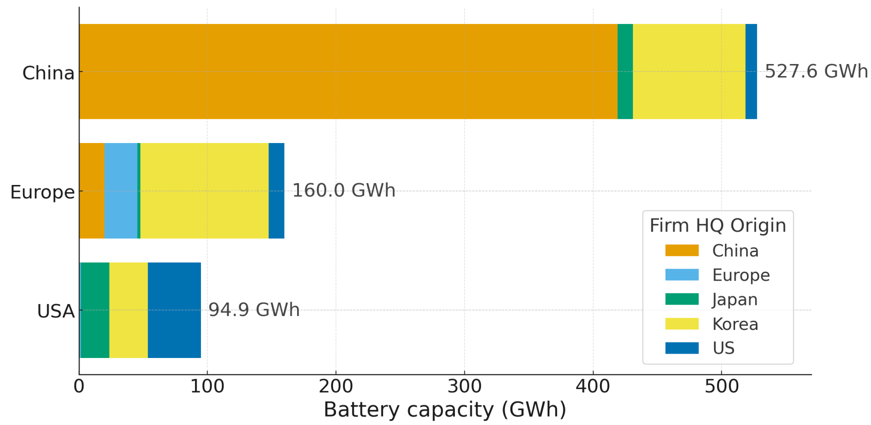
Batteries are a key component in EV production, accounting for 30-40% of the vehicle's total value. Most EVs rely on lithium-ion batteries, which are mainly based on one of three chemistries: nickel manganese cobalt (NMC), nickel cobalt aluminum (NCA) and lithium iron phosphate (LFP). Among them, NMC batteries have higher energy density but are more expensive due to their reliance on nickel and cobalt, whereas LFP batteries are cheaper but have lower energy density. Reflecting these cost–performance trade-offs, NMC batteries are more prevalent in European and North American markets, while LFP batteries dominate in China. Because each chemistry involves distinct material requirements and processing, the choice of battery type shapes the structure of the associated supply chain.

The global battery supply chain is largely led by East Asian countries. The upstream stages – from material processing to manufacturing required for cell production – are dominated by China, which produces nearly all LFP materials and over three-quarters of nickel-based chemistries. South Korea and Japan follow as major producers, particularly for nickel-rich cathode materials. While most of this production remains concentrated in these countries, firms have begun establishing plants abroad to meet growing demand and regional policy requirements.

The downstream stages are also led primarily by Asian firms, where battery cells are assembled and packaged for use in EV production. However, the physical assembly of cells increasingly occurs closer to major EV markets. As shown in Figure 3, global lithium-ion cell production capacity is distributed in line with EV sales and battery demand[6], with the largest capacities in China, Europe,

[5]See Figure A1 in Appendix A

[6]See Figure A2 in Appendix A.




*Notes:* This figure exhibits total battery production capacities across regions as well as the composition of firms which own the facilities by their headquarters' country of origin in 2022. China has the largest capacities worldwide, followed by South Korea and Japan. *Data Source: Automotive Manufacturing Solution Lithium-ion Battery Gigafactory Database*

Figure 3: Lithium-Ion Battery Cell Production Capacity by Region and Firm Origin

and the United States, respectively.

The composition of the firms of origin owning the manufacturing capacity varies by country. Next to domestic firms, the largest foreign companies owning the capacity are from South Korea (LG Energy Solution, SK On, Samsung SDI) taking 17%, 62%, and 31% in China, Europe and United States, respectively in 2022. It is then followed by companies from Japan (Panasonic, Envision AESC). Still, companies from China (e.g., CATL, BYD) is dominant in the global level, taking 79% and 13% of capacity in home and Europe. The ownership composition of this capacity varies by region. In 2022, firms from South Korea—LG Energy Solution, SK On, and Samsung SDI—accounted for 17%, 62%, and 31% of total manufacturing capacity in China, Europe, and the United States, respectively. They are followed by Japanese companies such as Panasonic and Envision AESC. Chinese firms, notably CATL and BYD, remain the global leaders, holding roughly 79% of capacity in China and 13% in Europe.

### 2.4 The U.S. Inflation Reduction Act

As part of the largest investment in clean energy and climate action in U.S. history, the IRA offers New Clean Vehicle Credit (30D) which includes consumer subsidy for EV purchase up to $7,500 in the form of tax credit. Eligibility is conditional on both income cap and a domestic content requirement. Additional conditions include a manufacturer's suggested retail price (MSRP) cap and the requirement that final assembly occur in North America. To simplify the analysis, the MSRP cap is omitted from the model, and the final assembly requirement is represented through a non-tradable assumption for the EV sector. Empirically, this assumption is well supported: Horowitz et al. (2021) report that 90% of EVs sold in 2019 were assembled in the United States. Under the income cap, only households below specific thresholds[7] are eligible for the tax credit when purchasing EVs that meet the domestic content requirement. The latter stipulates that at least 50% of battery components must be manufactured or assembled in North America before 2024, with the required share increasing by 10 percentage points each year until reaching 100% by 2029.

These two conditions serve as policy tools designed to align private incentives with public objectives. The income cap broadens market access by financially supporting households that previously faced barriers to EV adoption due to high prices and the high-income elasticity of demand. This, in turn, encourages EV producers to develop entry-level models tailored to eligible consumers, contributing both to climate-change mitigation and to the diffusion of green technologies.

To serve these eligible consumers, however, EV firms must satisfy the policy's domestic input threshold. Meeting this requirement increases unit production costs, since sourcing domestic inputs is typically more expensive. Global battery producers benefit from economies of scale and have concentrated production in countries with large EV markets. Contrary to this, U.S. battery production capacity has historically been lower and this results in higher domestic prices relative to global levels. Moreover, the geographic concentration of green technologies in China has become a major driver of geopolitical rivalry with the U.S. The domestic content requirement thus aims to expand the U.S. battery sector, increase EV adoption, and enhance supply chain resilience by reducing dependence on foreign countries, mostly China. While the provision supports both domestic and foreign investment, it implicitly favors attracting FDI as it is more efficient in accelerating capability development than relying solely on indigenous innovation.

As part of a broader strategy to decouple from geopolitical rivals and compete in the development of new technologies, the policy includes a clause known as the Foreign Entity of Concerns (FEOC) restriction. These entities are defined as China, Russia, and North Korea, and the tax credits pro-

[7] $300,000 for married couples filing jointly, $225,000 for heads of household, and $150,000 for single filers

vided under the IRA are restricted when the supply chain includes battery components sourced from them. I, therefore, exclude China from the analysis.

## 3 Theoretical Framework

I develop a two-country general equilibrium model of international trade that captures the mechanism of the U.S. Inflation Reduction Act (IRA), along with the key features of electric vehicle (EV) market outlined in the previous section. The central mechanism of the means-tested subsidies and domestic content requirements operates through consumer heterogeneity and the transmission of demand responses through the multi-stage EV supply chain. Depending on these heterogeneous consumer responses, EV producers determine the share of domestically sourced batteries, and battery producers subsequently decide whether to serve the market through export or foreign direct investment (FDI).

In the model, consumers differ in their income levels. To reflect a feature of the IRA which provides subsidies in the form of income-based tax credits, the model incorporates progressive taxation and transfers (Benabou, 2002). With their resulting disposable income, consumers allocate spending across multiple sectors according to non-homothetic preferences (Caron et al., 2014; Comin et al., 2021; Duernecker et al., 2024).

On the production side, EV and battery producers are vertically linked in a multi-stage EV supply chain (Yi, 2010). Each stage features monopolistic competition with heterogeneous firms, as in Melitz (2003); Chaney (2008). Based on their productivity, EV producers choose their optimal consumer segment and determine the share of inputs sourced domestically versus imported (Nigai, 2025; Blaum et al., 2018). Given differences in market demand across modes of serving foreign markets, battery producers then decide whether to export or engage in FDI based on the proximity-to-concentration trade-off (Brainard, 1997; Markusen, 2002; Helpman et al., 2004).

### 3.1 Taxation

Consider $L$ consumers, indexed by $\varphi$. Each consumer is endowed with $l(\varphi)$ units of labor, where the average endowment is one unit. Individuals supply labor inelastically at the wage rate $w$. Labor is perfectly mobile across sectors within a country but immobile across countries.

Consumer $\varphi$ earns pre-tax income $y(\varphi)$ defined as $y(\varphi) = l(\varphi) \cdot w + dd + tt$, where $dd$ and $tt$ denote average dividend income and tariff revenue, respectively. After taxes and transfers, disposable income $y^d(\varphi)$ is determined by a non-linear function with progressivity parameter $\rho$:

$$y^d(\varphi) = y(\varphi)^{1-\rho}(\tilde{y})^{\rho} \tag{1}$$

The degree of redistribution increases with $\rho \in [0,1]$. As $\rho \to 1$, disposable income becomes fully equalized across consumers while no distribution occurs when $\rho \to 0$. The break-even income level $\tilde{y}$ satisfies the government budget balance condition:

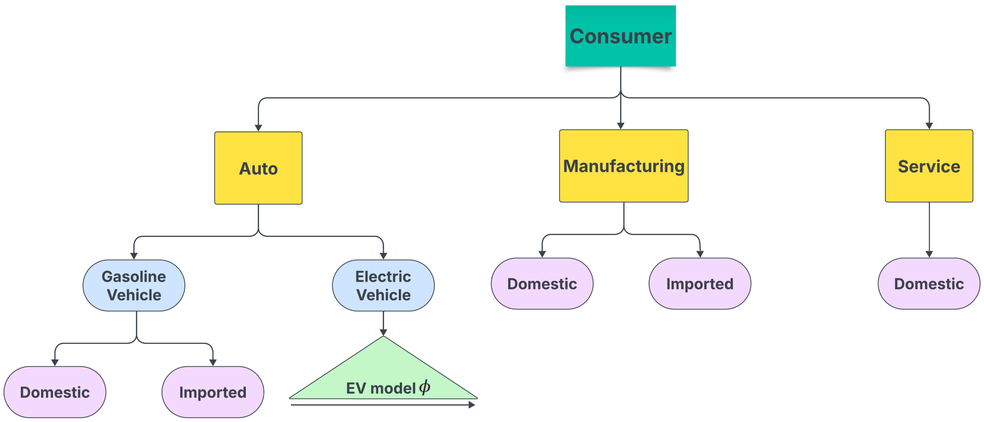
$$\int_{\varphi} y(\varphi) d\varphi = \int_{\varphi} y(\varphi)^{1-\rho}(\tilde{y})^{\rho} d\varphi + G \tag{2}$$

where total pre-tax income equals total disposable income plus government spending, $G$. After the policy intervention, $G > 0$ represents government expenditure on means-tested subsidies for EV purchases, financed by tax reveneus. In the baseline model, $G = 0$.

## 3.2 Consumer Preferences

I assume three nested non-homothetic CES demand system. Figure 4 summarizes the structure of a consumer $\varphi$'s demand in a consumption tree. Consumers spend their disposable income on final goods – auto, manufacturing goods and service– where auto sector is divided into gasoline vehicle (GV) and EV industries. EV industry is composed of a continuum of vehicle models in a imperfectly competitive market. On the other hand, manufacturing, service sectors and GV industry are perfectly competitive. Also, both service sector and EV industry are assumed to be non-tradable.

In this demand system, consumers choose purchases to maximize their aggregate consumption (utility), $u(\varphi)$. In doing so, they substitute between EVs and GVs, as well as across EV models, according to their income elasticity of demand and preferences for quality. I first present demand system for EVs and then proceed to describe the demand for other sectors.




*Notes:* This diagram illustrates the consumption tree of a consumer, $\varphi$, who has a three-tiered non-homothetic CES preference structure. Only the service sector and the electric vehicle (EV) industry are non-tradable. The consumer allocates disposable income, $y^d(\varphi)$, across vehicles (auto), manufactured goods, and services. Within the vehicle category, the consumer can substitute between gasoline vehicles and EVs, as well as across EV models, $\phi$. All other sectors and industries consist of domestic and imported aggregate goods.

Figure 4: Consumption Tree of Consumer $\varphi$

**Demand for EVs** In the upper tier, consumers allocate their disposable income across auto ($k = a$), manufacturing ($k = m$) and service ($k = s$) sector.

$$u(\varphi) = \left( \sum_{k=a,m,s} \gamma_k^{\frac{1}{\sigma_1}} c_k(\varphi)^{\frac{\sigma_1 - 1}{\sigma_1}} u(\varphi)^{\frac{\epsilon_k - 1}{\sigma_1}} \right)^{\frac{\sigma_1}{\sigma_1 - 1}} \tag{3}$$

In the middle tier, they choose between GVs ($k = g$) and EVs ($k = e$) within the auto sector.

$$c_a(\varphi) = \left( \sum_{k=g,e} \gamma_k^{\frac{1}{\sigma_2}} c_k(\varphi)^{\frac{\sigma_2 - 1}{\sigma_2}} u(\varphi)^{\frac{\epsilon_k - 1}{\sigma_2}} \right)^{\frac{\sigma_2}{\sigma_2 - 1}} \tag{4}$$

$\gamma_k$ are the demand shifters, where $\gamma_k = 1$ for all $k$, except for $\gamma_e \neq 1$. Also, $\sigma_1, \sigma_2 > 0$ are the elasticities of substitution between sectors in upper and middle tier, respectively while $\epsilon_k > 0$ captures the income effects in sector $k$. The parameters should meet the constraints $(\epsilon_k - \sigma_1)/(1 - \sigma_1) > 0$ for $k = a, m, s$ in the upper tier and $(\epsilon_k - \sigma_2)/(1 - \sigma_2) > 0$ for $k = g, e$ in the middle tier.

In the bottom tier, consumers choose EV models, indexed by $\phi$, within the EV industry as:

$$c_e(\varphi) = \left( \int \lambda(\varphi, \phi)^{\frac{1}{\sigma_3}} c_e(\varphi, \phi)^{\frac{\sigma_3 - 1}{\sigma_3}} d\phi \right)^{\frac{\sigma_3}{\sigma_3 - 1}} \tag{5}$$

where $\sigma_3 > 1$ is the elasticity of substitution between EV models. The non-homotheticity of the demand in this tier is specified as a demand shifter $\lambda(\varphi, \phi)$ which captures consumer tastes for quality that are consistent with their income level – higher-income consumers prefer higher-quality models. Further discussion of $\lambda(\varphi, \phi)$ is provided below.

Solving the maximization problems of (3), (4), (5) lead to $\varphi$'s demand for an EV model $\phi$:

$$c_e(p(\phi); \varphi) = \lambda(\varphi, \phi) \Big( \frac{p(\phi)}{P_e(\varphi)} \Big)^{-\sigma_3} c_e(\varphi), \tag{6}$$

$$\text{where} \quad c_e(\varphi) = \gamma_e P_e(\varphi)^{-\sigma_2} P_a(\varphi)^{\sigma_2 - \sigma_1} P(\varphi)^{\sigma_1} u(\varphi)^{\epsilon_e + \epsilon_a - 1}$$

$c_e(\varphi)$ is consumer $\varphi$'s aggregate consumption in the EV industry and $p(\phi)$ is the price of an EV model $\phi$. The price indices for EV industry, $P_e(\varphi)$, auto sector, $P_e(\varphi)$, together with the aggregate price index, $P(\varphi)$, are specified as

$$P_e(\varphi) = \Big( \int_\varphi \lambda(\varphi, \phi) p(\phi) d\phi \Big)^{\frac{1}{1-\sigma_3}},$$

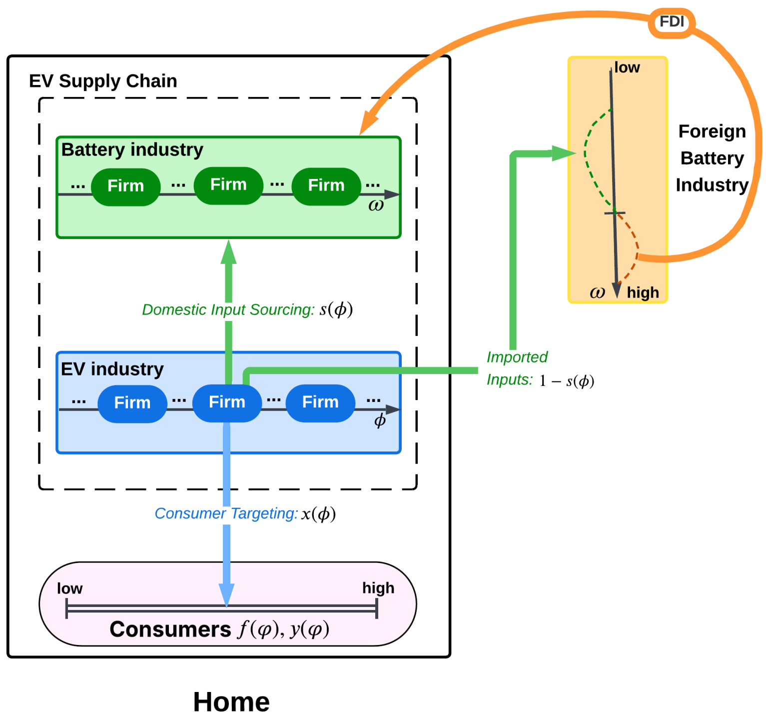
$$P_a(\varphi) = \Big( \sum_{k=g,e} \gamma_k c_k(\varphi)^{\epsilon_k - 1} P_k(\varphi)^{1-\sigma_2} \Big)^{\frac{1}{1-\sigma_2}}$$

$$P(\varphi) = \Big( \sum_{k=a,m,s} \gamma_k c_k(\varphi)^{\epsilon_k - 1} P_k(\varphi)^{1-\sigma_1} \Big)^{\frac{1}{1-\sigma_1}}$$

**Demand for Other Sectors** For all other sectors, the upper tier is the same as the equation (3). The nests below manufacturing sector and GV industry in country $i$ consist of domestic and imported goods, each of which is specified as $c_{ik}(\varphi) = \Big( \sum_j c_{jik}(\varphi)^{\frac{\sigma_3 - 1}{\sigma_3}} \Big)^{\frac{\sigma_3}{\sigma_3 - 1}}$ for $k = m, g$, where $c_{jim}(\varphi) = \Big( \frac{P_{jim}}{P_i(\varphi)} \Big)^{-\sigma_1} u(\varphi)^{\epsilon_m - 1}$, $c_{jig}(\varphi) = \Big( \frac{P_{jig}}{P_{ia}(\varphi)} \Big)^{-\sigma_2} \Big( \frac{P_{ia}}{P_i(\varphi)} \Big)^{-\sigma_1} u(\varphi)^{\epsilon_g + \epsilon_a - 1}$ and $c_{is}(\varphi) = \Big( \frac{P_{is}}{P_i(\varphi)} \Big)^{-\sigma_1} u(\varphi)^{\epsilon_s - 1}$.

### 3.3 Multi-Stage Production

In this section, I describe how EV firms and battery firms are connected through a multi-stage EV supply chain. As illustrated in Figure 5, domestic EV firms optimally choose to link with both consumers and the battery industry, while foreign battery firms, in turn, determine their mode of serving the domestic EV market. For convenience, I denote the EV firm and the EV model it produces by $\phi$, and the battery firm and the variety it produces by $\omega$.




*Notes:* This diagram illustrates the electric vehicle (EV) market, including the multi-stage production structure of the EV supply chain in home country. It summarizes the mechanism through which the EV market and supply chain are shaped by the decisions of domestic EV firms and foreign battery producers. Domestic EV firms endogenously target consumer segments by choosing $x(\phi)$ and determine the domestic sourcing share of batteries, $s(\phi)$. In response to demand from the home country, foreign battery producers choose whether to export or undertake foreign direct investment.

Figure 5: Firm Choices in Multi-Stage Production

### 3.3.1 Electric Vehicle Production

Consider $N_e$ firms, each producing a unique EV model $\phi$ and operating only in its home country. The problem of an EV firm is twofold: $(i)$ it decides which income group to target as its primary consumers; $(ii)$ it chooses the share of intermediate inputs – batteries – sourced domestically. I assume there are no fixed costs associated with entry into importing, allowing every firm to rely on imported batteries for at least a certain share of production. This assumption is not unreasonable, given that the focus is on U.S. EV production, where most firms depend on foreign batteries as key inputs.

**Consumer Targeting** There is a vector of $D$ dimensional product attributes of EVs and firm $\phi$ chooses the linear combination of these attributes denoted by $x(\phi)$ to target consumers.

$$x(\phi) = \xi(\phi)^T, \text{ where } \mathbb{X}(\phi) : \mathbb{R}^D \to \mathbb{R}^+ \tag{7}$$

Note that consumers' tastes are characterized by attributes of the ideal product for $\varphi$ that is denoted by $f(\varphi) : \mathbb{R} \to [0, 1]$. Then the demand shifter is characterized as

$$\lambda(f(\varphi), x(\phi); \delta) = \Big[1 + \delta\big(f(\varphi) - x(\phi)\big)^2\Big]^{-1} \tag{8}$$

where $\delta$ denotes the rate at which quadratic deviations from the most preferred characteristics lower utility for consumer $\varphi$. That is, the distance between $f(\varphi)$ and $x(\phi)$, together with $\delta$ represent how much demand will be collect around the target consumer segment. If $f(\varphi) = x(\phi)$, the demand of $\varphi$ for $\phi$ is the largest conditional on $p(\phi)$. If $f(\varphi) \neq x(\phi)$ and the deviation gets bigger, $\varphi$'s demand for $\phi$ becomes smaller which means that $\phi$ is only picking up partial amount of demand of $\varphi$.

When firms target consumer segments, they know, by assumption, that consumers with higher pre-tax income have higher measure of taste $f(\varphi)$ and higher fixed costs are needed to target the higher income consumers. This is because relatively larger resources should be put to figure out their tastes and thus only firms with higher productivity can target them.

**Input Sourcing Decision** Consider following production functions of an EV firm $\phi$:

$$y(\phi) = \phi \cdot l(\phi)^{1-\alpha} z(\phi)^{\alpha} \tag{9}$$

$$z(\phi) = \left(z_H^{\frac{\eta-1}{\eta}} + z_F\big(\Omega(\phi)\big)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \tag{10}$$

$$z_F\big(\Omega(\phi)\big) = \left(\int_{\Omega(\phi)} m(\omega)^{\frac{\kappa-1}{\kappa}} d\omega\right)^{\frac{\kappa}{\kappa-1}} \tag{11}$$

where $\eta, \kappa > 1$ are the elasticity of substitution between the composite input sourced domestically and abroad, and across imported input varieties, respectively. To produce an EV model, firm $\phi$

combines labor $l(\phi)$ and an intermediate input bundle $z(\phi)$, with $\alpha \in (0,1)$ representing the share of $z(\phi)$. The input bundle $z(\phi)$ consists of domestically produced composite batteries, $z_H$, and imported composite batteries, $z_F\big(\Omega(\phi)\big)$. Both $z_H$ and $z_F\big(\Omega(\phi)\big)$ are aggregates of demand for battery varieties, $m(\omega)$, combined using a CES function. While all domestic varieties are sourced by all domestic firms, imported varieties are endogenously selected by each firm $\phi$, which is characterized by its sourcing strategy $\Omega(\phi)$.

The price index for the input bundle is specified as

$$Q(\Omega(\phi)) = \Big(q^{1-\eta} + A\big(\Omega(\phi)\big)^{1-\eta}\Big)^{\frac{1}{1-\eta}} \tag{12}$$

where $q$ and $A\big(\Omega(\phi)\big)$ are the price index for the domestically produced and imported composite batteries, respectively. To specify $A\big(\Omega(\phi)\big)$, $\Omega(\phi)$ should be defined first.

The sourcing strategy, $\Omega_j(\phi_i)$, is defined as the set of foreign battery varieties, $\omega$, imported by domestic firm $\phi$. When the firm chooses the least efficient variety, $\bar{\omega}$, that it is willing to import, then the set is endogenously determined as all varieties that are more efficient than $\bar{\omega}$. Then, the sourcing strategy of the firm $\phi_i$ in country $i$ is specified as:

$$\Omega(\phi_i) = \{\omega_j | \omega_j \geq \bar{\omega}_j(\phi_i) \text{ and } \omega_j \leq \omega_j^I\}$$

where $\omega_j^I$ is a given productivity cutoff for battery firms in country $j$, choosing FDI over export when serving foreign market.

With the definition of the sourcing strategy and the distribution assumption on the productivity of battery firms, the price index for imported composite batteries, $A\big(\Omega(\phi)\big)$ can be defined. Suppose that battery firms are distributed as Pareto with the shape parameter $\theta$, such that $Pr(\bar{\omega}_j(\phi) \leq \omega) =$

$1-(\omega_{\min}/\omega)^{\theta}$ where $\theta > \min[1, \kappa-1]$. Then, $A(\Omega(\phi))$ can be expressed as

$$
\begin{aligned}
A\big(\Omega(\phi)\big) =& \Big(\int_{\Omega(\phi)} \Big[\frac{\kappa}{\kappa-1}\frac{w\tau}{\omega}\Big]^{1-\kappa} d\omega\Big)^{\frac{1}{1-\kappa}} \\
=& \begin{cases} 0 & \text{if } \bar{\omega}(\phi) > \omega^I \\ a\cdot\Big[n(\phi)^{1+\frac{1-\kappa}{\theta}} - (n^{I*})^{1+\frac{1-\kappa}{\theta}}\Big]^{\frac{1}{1-\kappa}} & \text{if } \bar{\omega}(\phi) \leq \omega^I \end{cases} \\
\equiv& A\big(n(\phi)\big)
\end{aligned} \tag{13}
$$

where $\omega^I$ is the FDI cutoff and $a$ is a constant.[8] $n(\phi)$ and $n^{I*}$ are the share of the foreign battery varieties imported and produced domestically, respectively[9]. Given the parameter constraints, the price of imported composite batteries can be expressed as a function of $n(\phi)$ and decreases as the firm sources larger share of foreign varieties.

Then, given the constant returns to scale production function, the unit cost and the domestic input share is specified as

$$
uc\big(\Omega(\phi)\big) = \frac{w^{1-\alpha}Q\big(n(\phi)\big)^{\alpha}}{\phi}, \quad s(\phi) \equiv s\big(n(\phi)\big) = \bigg(\frac{q}{Q\big(n(\phi)\big)}\bigg)^{1-\eta} \tag{14}
$$

By combining two equations in (14), the unit cost $uc\big(n(\phi)\big)$ can be expressed with $s(\phi)$ without the need to specify the share of foreign battery vareities imported, $n(\phi)$, as well as the price indices $Q(n(\phi))$ and $A(n(\phi))$.

$$
uc(\phi) = \frac{w^{1-\alpha}}{\phi}\Big(q\cdot s(\phi)^{\frac{1}{\eta-1}}\Big)^{\alpha}
$$

**Profit Maximization Problem** Note that consumers ranked as $f(\varphi)$ according to their taste and income are characterized by the cumulative density function (c.d.f.) of $H(\varphi)$. Then, given $c_e\big(f(\varphi), x(\phi), p(\phi); \varphi\big)$ in equation (6), the aggregate demand that firm $\phi$ faces is specified as

$$
C_e\big(p(\phi), x(\phi)\big) = p(\phi)^{-\sigma_3} v(x(\phi)), \text{ where } v(x(\phi)) = L\int_{\varphi} \frac{P_e(\varphi)^{\sigma_3} c_e(\varphi)}{1+\delta\big(f(\varphi)-x(\phi)\big)^2} dH(\varphi) \tag{15}
$$

[8]The constant $a_{ji}$ is specified as $a_{ji} = \omega_{j,\min}^{-1}\Big(\frac{N_{jb}\theta}{\theta-(\kappa-1)}\Big)^{\frac{1}{1-\kappa}}\frac{\kappa}{\kappa-1}w_j\tau_{ji}$

[9]See Appendix B for further details about the derivation.

where $L$ is the total number of consumers. Then, the profit function can be expressed as

$$\pi_e(p(\phi), x(\phi)) = p(\phi)C_e(p(\phi), x(\phi)) - uc(\phi)C_e(p(\phi), x(\phi)) - \mathcal{C}(\phi) \tag{16}$$

where $\mathcal{C}(\phi)$ is a simplified notation for $\phi$'s sourcing cost plus targeting cost. Maximizing the profit function with respect to $p(\phi)$ leads to constant mark-up pricing:

$$p(\phi) = \frac{\sigma_3}{\sigma_3 - 1}\frac{w^{1-\alpha}}{\phi}\left(q \cdot s(\phi)^{\frac{1}{\eta-1}}\right)^{\alpha} \tag{17}$$

Plugging $p(\phi)$ back into the profit function yields the firm's optimization problem, where firm $\phi$ $(i)$ chooses the domestic input share, $s(\phi)$, and $(ii)$ targets the consumer base, $x(\phi)$. The profit function to be optimized is specified as follows:

$$\pi_e\big(s(\phi), x(\phi)\big) = \frac{L}{\sigma_3}\Big(\frac{\sigma_3}{\sigma_3 - 1}\frac{w^{1-\alpha}q^{\alpha}}{\phi}\Big)^{1-\sigma_3} s(\phi)^{\frac{\alpha(1-\sigma_3)}{\eta-1}} v(x(\phi)) - wf^{im}SC\big(s(\phi)\big) - TC\big(x(\phi)\big)$$

where $SC\big(s(\phi)\big)$ denotes the sourcing cost, measured in labor units and associated with the number of input varieties imported. $f^{im}$ is a scale parameter that governs the baseline level of this cost. $TC\big(x(\phi)\big)$ is the cost for targeting consumer base specified as $b \cdot x(\phi)^{\beta}$ where $b$ is a constant and $\beta \geq 3$ so that marginal cost of elevating target consumer costs is strictly convex.

To be specific about the sourcing cost, it is more intuitive to express it as $SC\big(n(\phi)\big)$ since it implies such costs paid to search appropriate varieties and make contracts when importing from foreign producers: $SC\big(n(\phi)\big) = n(\phi)^{1+\frac{1-\kappa}{\theta}} - (n^{I*})^{1+\frac{1-\kappa}{\theta}}$. However, to keep the optimization problem simple as possible, it can be summarized as a function of the domestic input share $s(\phi)$ based on equation (13) and (14): $SC\big(s(\phi)\big) = \left(\frac{1-s(\phi)}{s(\phi)}\right)^{\frac{1-\kappa}{1-\eta}}\left(\frac{q}{a}\right)^{1-\kappa}$.[10] As such, since $SC\big(s(\phi)\big)$ is proportional to the range imported battery varieties, it decreases as the firm sources a larger share of inputs domestically – that is, as $s(\phi)$ increases.

The trade-offs that firms face when choosing $\{s(\phi), x(\phi)\}$ are as follows. First, imported inputs entail higher costs due to expenses associated with search, contracting, and coordination frictions, yet they enable firms to lower unit production costs, which drives the price down. Therefore, more

[10] See for detailed derivation in Appendix B.

productive firms tend to rely more on foreign batteries, taking advantage of economies of scale. In addition, targeting higher-income consumers is more costly, as they have more luxurious tastes, requiring firms to incur higher costs to enhance product quality. Moreover, they represents only a relatively small share of the population. Nevertheless, firms can benefit from their higher average expenditure levels. Based on these trade-offs, optimal domestic input share and target consumer base, $\{s^*(\phi), x^*(\phi)\}$, are chosen as:

$$\{s^*(\phi), x^*(\phi)\} = \underset{s(\phi),x(\phi)}{\arg\max} \Big\{ \pi_e(s(\phi), x(\phi)) \Big\} \tag{18}$$

### 3.3.2 Battery Production

From this section, I introduce the subscript $i, j$ to denote countries. Let's assume $i$ as home and $j$ as foreign country. There are $N_b$ number of battery firms each of which produces a unique battery variety $\omega$. The batteries are used only as a key input of EV model, meaning that they are excluded from the final consumption. Consider the battery sector as tradable and I assume all firms are potential exporters. This means that no fixed cost is charged to initiate exporting goods since it is paid by the EV firms when they import batteries (Antras et al., 2017).

Note that this section introduces *Foreign* battery firm $\omega_j$'s problem given $\phi_i$'s decisions in *Home*. All firms operating in the industry serve domestic market through domestic production. They can also serve consumers in the foreign market either through exporting or making FDIs (Helpman et al., 2004). The choice depends on the proximity–concentration trade-off (Brainard, 1997; Markusen, 2002), where FDI reduces trade costs but entails fixed costs of establishing a new production site, relative to exporting. I allow the market size across modes of serving foreign consumers to varyso that the extent of economies of scale can be assessed from both the demand and supply side.

Let's start with identifying the profit function when $\omega_i$ chooses to export. Given the aggregate demand index for exports that $\omega_i$ faces, $DX_{ij}(\omega_i)$, the potential profit can be specified as

$$\pi^X_{ijb}(\omega_i) = \frac{1}{\kappa}\Big(\frac{\kappa}{\kappa-1}\frac{w_i\tau_{ijb}}{\omega_i}\Big)^{1-\kappa} DX_{ij}(\omega_i), \tag{19}$$

$$\text{where} \quad DX_{ij}(\omega_i) = N_{je}\int_{\phi_j\in\Phi(\omega_i)} q_i\big(\Omega(\phi_j)\big)^{\kappa-1}(1-s(\phi_j))E_j(\phi_j)dF_j(\phi_j) \tag{20}$$

where $w_j$ is the cost of an input bundle and $\tau_{ijb} = (1+t_{ijb})d_{ijb}$ is the trade cost of exporting batteries from $i$ to $j$ which consists of ad-valorem tariff rate $t_{ijb}$ and iceberg cost $d_{ijb} > 1$. $E^{im}_j(\phi_j)$ is the total expenditure of $\phi_j$ on imported batteries[11] and $q_i\big(\Omega_i(\phi_j)\big)$ is the price index for composite battery inputs. $\Phi_j(\omega_i) = \{\phi_j|\omega_i \in \Omega(\phi_j)\}$ is a set of EV firms in *Foreign* $(j)$ that $\omega_i$ exports batteries to. Likewise, given the aggregate demand index for domestically produced batteries in *Foreign* $(j)$, $DD_j$, the potential profit function when $\omega_i$ chooses to make FDI in *Foreign* $(j)$ is

$$\pi^I_{ijb}(\omega_i) = \frac{1}{\kappa}\Big(\frac{\kappa}{\kappa-1}\frac{w_j}{\omega_i}\Big)^{1-\kappa} DD_j - w_j f^I_j \quad \text{where } DD_j = N_{je}\int_{\phi_j} q_j^{\kappa-1}s(\phi_j)E_j(\phi_j)dF_j(\phi_j) \tag{21}$$

$f^I_j$ is the fixed cost of establishing a production site in $j$ in unit of labor. $E_j(\phi_j)$ and $q_j$ are the total expenditure and the price index of domestically produced batteries, respectively. These are not $\omega$-specific since EV firms source from all domestically produced batteries. In align with this, the profit of $\omega_i$ obtained by operating in domestic market is $\pi^D_{ib}(\omega_i) = \frac{1}{\kappa}\Big(\frac{\kappa}{\kappa-1}\frac{w_i}{\omega_i}\Big)^{1-\kappa} DD_i$. Then, the choice rule can be set as

$$\text{Firm } \omega_i \begin{cases} \text{exports} & \text{when } \pi^X_{ijb}(\omega_i) > \pi^I_{ijb}(\omega_i) \\ \text{make an FDI} & \text{when } \pi^X_{ijb}(\omega_i) \le \pi^I_{ijb}(\omega_i) \end{cases} \tag{22}$$

where $\omega^X_i$ and $\omega^I_i$ are a set of firms in $i$ exporting and making FDIs, respectively.

[11] $E_j(\phi_j) = \alpha\frac{\sigma_3-1}{\sigma_3}r_{je}(\phi_j)$ where $r_{je}(\phi_j)$ is the operating revenue of $\phi_j$ defined as

$$r_{je}(\phi_j) = L_j\Big(\frac{\sigma_3}{\sigma_3-1}w_j^{1-\alpha}(q^H_j)^\alpha\Big)^{1-\sigma_3}\phi_j^{\sigma_3-1}s^*_j(\phi)^{\frac{\alpha(1-\sigma_3)}{\eta-1}}v(x^*_j(\phi))$$

### 3.4 Equilibrium

In this section, I specify the aggregate variables of EV and battery sectors. Refer to Appendix B for other sectors' variables (auto, manufacturing and service). Note that the mass of firms in EV and battery sector is $N_{ie}$ and $N_{ib}$ respectively. For simplicity, I assume that the firms neither enter nor exit. This means that zero profit condition is not binding in this model. The c.d.f. of $\phi$ and $\omega$ are denoted by $F(\phi)$ and $M(\omega)$. Then, given the individual firm's optimal profit and optimal mode of serving foreign firms, the aggregate profits are specified as:

$$\Pi_{ie} = N_{ie} \int_{\phi} \pi_{ie}\big(\phi, s^*(\phi), x^*(\phi)\big) dF_i(\phi) \tag{23}$$

$$\Pi_{ib} = N_{ib} \left\{ \int_{\omega_i} \pi_{ib}^{D}(\omega_i) dM_i(\omega_i) + \int_{\omega_i \in \omega_i^X} \pi_{ijb}^{X}(\omega_i) dM_i(\omega_i) + \int_{\omega_i \in \omega_i^I} \pi_{ijb}^{I}(\omega_i) dM_i(\omega_i) \right\} \tag{24}$$

The price indices for EV sector, $P_{ie}(\varphi)$, and for battery sector, $q_i^d$ are specified as

$$P_{ie}(\varphi)^{1-\sigma_3} = N_{ie} \Big( \frac{\sigma_3}{\sigma_3 - 1} w_i^{1-\alpha} (q_i^H)^{\alpha} \Big)^{1-\sigma_3} \int_{\phi_i} \left[ 1 + \delta\big(f_i(\varphi) - x_i^*(\phi)\big)^2 \right]^{-1} s_i^*(\phi)^{\frac{\alpha(1-\sigma_3)}{\eta - 1}} \phi^{\sigma_3 - 1} dF_i(\phi) \tag{25}$$

$$(q_i)^{1-\kappa} = \Big( \frac{\kappa}{\kappa - 1} w_i \Big)^{1-\kappa} \left[ N_{ib} \int_{\omega} \omega_i^{\kappa-1} dM_i(\omega) + N_{jb} \int_{\omega_j \in \omega_j^I} \omega_j^{\kappa-1} dM_j(\omega) \right] \tag{26}$$

Equation (25) shows that the average EV price that consumer $\varphi$ faces differs by $i$) the matching between her taste and EV firm $\phi$'s targeting and $ii$) the domestic input share used by the firm. It is relatively easy to understand that a specific $\phi$'s increased use of domestic batteries raises the overall price index for $\varphi$. However, the extent of the effect of the same price increase would actually impact the price index for consumers differently. If the $\phi$ is targeting higher-income consumers, then their price index will be more adversely affected than lower-income consumers'. Equation (26) is the price index for domestically produced batteries and it falls if more firms from $j$ decide to build production sites in $i$.

Aggregate expenditure and export flows from $i$ to $j$ with tariff can be characterized by as follows:

$$X_{ie} = \int_{\varphi} \frac{\int_{\phi_i} s_i^*(\phi)^{\frac{\alpha(1-\sigma_3)}{\eta-1}} \phi^{\sigma_3-1} dF_i(\phi)}{\int_{\phi_i} \left[1+\delta\big(f_i(\varphi)-x_i^*(\phi)\big)^2\right]^{-1} s_i^*(\phi)^{\frac{\alpha(1-\sigma_3)}{\eta-1}} \phi^{\sigma_3-1} dF_i(\phi)} L_i P_{ie}(\varphi) c_{ie}(\varphi) dH_i(\varphi) \tag{27}$$

$$X_{iib} = N_{ie} \int_{\phi} s_i^*(\phi) \cdot r_{ie}\big(\phi_i, s_i^*(\phi_i), x_i^*(\phi_i)\big) dF_i(\phi) \tag{28}$$

$$X_{ijb} = N_{je} \int_{\phi} \big(1 - s_j^*(\phi)\big) \cdot r_{je}\big(\phi_j, s_j^*(\phi_j), x_j^*(\phi_j)\big) dF_j(\phi) \tag{29}$$

Next, I describe how the pre-tax household income $y_i(\varphi)$ is determined. As explained at the beginning of section 3, consumers differ their labor endowment $l_i(\varphi)$. On average, each consumer possess one unit of labor such that $\int_{\varphi} l_i(\varphi) dH_i(\varphi) = 1$. Besides the labor income, consumers also earn dividend $dd_i$ from firm profits and tariff revenue $tt_i$ collected from battery trade:

$$y_i(\varphi) = l_i(\varphi) w_i + dd_i + tt_i, \quad \text{where} \begin{cases} dd_i = \frac{1}{L_i}(\Pi_{ie} + \Pi_{ib}) \\ tt_i = \frac{1}{L_i} t_{ijb} \frac{X_{ijb}}{1+t_{ijb}} \end{cases} \tag{30}$$

Since there is only one country to collect the tariff from, I let the tariff revenue per consumer to be $tt_i$ instead of $tt_{ij}$. Then, with the price indices for the rest of the sectors in Appendix B, the aggregate price index is expressed as

$$P_i(\varphi) = \left( \sum_{k=a,m,s} \gamma_{ik} \cdot u_i(\varphi)^{\epsilon_k - 1} P_{ik}(\varphi)^{1-\sigma_1} \right)^{\frac{1}{1-\sigma_1}} \tag{31}$$

Again, with the total export flows for the rest of the sectors, I close the model by specifying the trade balance condition:

$$\sum_j \sum_k \frac{X_{ijk}}{1+t_{ijk}} + D_i = \sum_j \sum_k \frac{X_{jik}}{1+t_{jik}} \tag{32}$$

where $k \in \{m, s, g, e, b\}$ and $D_i$ is an exogenous deficit constant. Also, only $t_{ijb} > 0$ while tariff for other sectors are all zeros. Through the equation (32), wage is determined.

**Definition:** *Given sets of economic fundamentals* $\mathbb{C} = \{\rho, H(\varphi), \sigma_1, \sigma_2, \sigma_3, \epsilon_a, \epsilon_m, \epsilon_s, \epsilon_g, \epsilon_e, \gamma\}$, $\mathbb{F} = \{\alpha, \eta, \kappa, \delta, \beta, b, t_{ijb}, d_{ijb}, F_i(\phi), M_i(\omega), f_i^{im}, f_i^I\}$ *and* $\mathbb{O} = \{A_{im}, A_{is}, A_{ig}, L_i, \tau_{ij}, N_{ie}, N_{ib}\}$, *an equilibrium is a vector of wage and price index* $\{w_i, P_i(\varphi)\}$ *that satisfies equation (18), (22), (23), (24), (25), (26),* *(27), (28), (29), (30), (31), and (32) for all $\varphi_I$, $\phi_i$, $\omega$, i and j.*

## 4 Policy Intervention

I benchmark the U.S. IRA to construct two policy interventions: (i) a consumer subsidy rate, $S$, and (ii) a domestic input requirement, $T$. The subsidy is subject to eligibility conditions, as only households within a certain income range qualify. Likewise, the domestic input requirement serves as an eligibility condition for EV producers. Both policies are implemented only in *Home*.

First, I define $\tilde{y}$ in equation (2) as the income cutoff for eligible consumers. As a constant that ensures government budget balance, $\tilde{y}$ also represents the threshold distinguishing consumers who receive a net transfer from those who pay a net tax. Hence, $\tilde{y}$ serves as an appropriate cutoff to identify the low- to middle-income consumers targeted by the policy.

$$\begin{cases} y(\varphi) \leq \tilde{y} : \varphi \text{ receives a net transfer} & \Rightarrow \varphi \in \varphi^E : \text{ Eligible} \\ y(\varphi) > \tilde{y} : \varphi \text{ pays a net tax} & \Rightarrow \varphi \in \varphi^I : \text{ Ineligible} \end{cases} \tag{33}$$

After applying the subsidy rate, the effective price of an EV model faced by consumers becomes $p'(\phi)$, creating a wedge between the consumer price and the firm price, $p(\phi)$.

$$p'(\phi) = (1 - S) \cdot p(\phi), \quad S = \begin{cases} \in (0, 1), & \text{if } \varphi \in \varphi^E, \phi \in \phi^E \\ 0, & \text{otherwise} \end{cases} \tag{34}$$

Then, government spending $G > 0$ in equation (2) is defined as the total amount of subsidies:

$$G = \int_{\phi \in \phi^E} S \cdot p(\phi) \cdot C_e\big(p'(\phi), x(\phi)\big) \tag{35}$$

where $C_e\big(p'(\phi), x(\phi)\big)$ is the aggregate demand for $\phi$ in equation (15).

Given consumers' choices in EV adoption, an EV firm should also decide whether to comply with the policy $T$. If it complies, the EV model it produces become eligible for subsidies when purchased by qualifying consumers. The firm's decision is made in two steps. First, it computes potential profit levels when it is eligible, $\pi^E(\phi)$ and when it is ineligible, $\pi^I(\phi)$. It then chooses the option that yields the higher profit.

$$\text{Step 1.} \quad \pi^E(\phi) = \max_{s(\phi),x(\phi)} \pi(s(\phi), x(\phi)) \quad \text{s.t} \quad s(\phi) \geq T$$

$$\pi^I(\phi) = \max_{s(\phi),x(\phi)} \pi(s(\phi), x(\phi)) \quad \text{s.t} \quad s(\phi) < T$$

$$\text{Step 2.} \quad \phi = \begin{cases} \phi^E & \text{if } \pi^E(\phi) \geq \pi^I(\phi) \\ \phi^I & \text{if } \pi^E(\phi) < \pi^I(\phi) \end{cases}$$

# 5 Quantitative Analysis

## 5.1 Calibration

I calibrate $Home(i)$ to the U.S. and $Foreign(j)$ to 13 developed countries in 2019[12]. There are three sets of key parameters: $\mathbb{C}, \mathbb{F},$ and $\mathbb{O}$, each of which denotes parameters related to consumers, firms and others respectively. Let's start with the parameters on the consumption side.

$$\mathbb{C} = \{\rho, H(\varphi), \sigma_1, \sigma_2, \sigma_3, \epsilon_a, \epsilon_m, \epsilon_s, \epsilon_g, \epsilon_e, \gamma\}$$

Tax progressivity $\rho$ is estimated based on the log-linear relationship between pre-tax income and disposable income in equation (1). Following Antràs et al. (2017), I use income distribution data from Congressional Budget Office. The data contains annual income before and after transfers and taxes for eight groups of U.S. households classified by the income level.[13] I estimate the average $\rho$ in 2019 and 2021 as 0.1887. In 2019 and 2021, $\rho$ is 0.175 and 0.2 with R-sqaured of 0.99. Since the degree of progressivity jumped in 2020 due to Covid-19, I smooth it out by using the data before and after. As a sensitivity check, I also conducted the estimation using different data; I employ Panel Study of Income Dynamics (PSID) with NBER TAXSIM to calculate the pre- and post-tax and transfer income according to Heathcote et al. (2017) and obtained similar result. Further information is in

[12]Countries for *Foreign* includes Austria, Belgium, France, Germany, Hungary, Italy, Poland, Spain, Slovakia, Sweden and United Kingdom, Japan and South Korea.

[13]Eight groups consist of four quintiles and the highest quintile divided into 81-90th, 91st-95th, 96th-99th percentiles and top 1%.

Appendix D.

Next, I assume Pareto income distribution, $H(\varphi)$. Data for the average income and the share of top 1% in total income are obtained from the World Inequality Database (WID). To combine the data for 13 developed countries as one *Foreign* country, I use Generalized Pareto Interpolation (Gpinter) program from WID which enables data from multiple countries to be interpolated and simulate one income distribution. With the data and the Pareto assumption of $H(\varphi) \sim (y_{min}, \sigma)$, I can recover the parameters as follows:

$$I_i = \int y dH_i(y) = \frac{\sigma}{\sigma - 1} y_{i,min} \quad S_i = \frac{1}{I_i} \int_{y_{99}} y H_i(y) = (0.01)^{\frac{\sigma-1}{\sigma}}$$

where $I_i$ and $S_i$ are the data for the average income and the share of top 1% in total income. $y_{99}$ is the income of $99^{th}$ percentile where $y_{99} = y_{min}(0.01)^{-1/\sigma}$.

For the price elasticity of substitution on the first tier in the non-homothetic preference, I assume that auto, manufacturing and services are complements ($\sigma_1 = 0.7$). It is known from structural change literature that manfuacturing and services are typically complements (Comin et al., 2021; Duernecker et al., 2024). Evidence on substitution between autos and the rest of manufacturing is mixed; some suggest price elasticity to be 0.87 (McCarthy, 1996) and others 1.14 (Attanasio et al., 2022). For the second tier, I assume EVs and GVs are substitutes as assumed in many EV adoption literature. I set it as $\sigma_2 = 2$. Lastly, in the third tier where EV models are aggregated, I set $\sigma_3 = 4.2$.

For the income elasticity, I assume that auto and service to be higher income elastic than manufacturing. Again, it is typical that richer population consumer more services so I set $\epsilon_s = 1.2$ when $\epsilon_m = 1$. On the other hand, literature reports that income elasticity on auto spans from 0.54 to 3.41 (McCarthy, 1996; Lui et al., 2013; Hummels and Lee, 2018; Linn and Shen, 2024). Based on the descriptive evidence showing that richer consumers have higher relative EV consumption than others in Figure 2, I set $\epsilon_a = 1.4$ and $\epsilon_e = 1.3$ when $\epsilon_g = 1$.

$$\mathbb{F} = \{\alpha, \eta, \kappa, \delta, \beta, b, t_{ijb}, d_{ijb}, F_i(\phi), M_i(\omega), f_i^{im}, f_i^I\}$$

Table 1: Calibrated Parameters

| Parameters | Value | Description | Data Source |
|---|---|---|---|
| *Consumption Parameters*, $\mathbb{C}$ | | | |
| $\rho$ | 0.1887 | Degree of tax progressivity | Congress Budget Office |
| $(y_{i,min}, y_{j,min})$ | (0.4324, 0.3568) | Income distribution (scale) | World Inequality Database |
| $(\sigma_i, \sigma_j)$ | (1.5629, 1.8060) | Income distribution (shape) | World Inequality Database |
| $\sigma_1$ | 0.7 | ES (auto vs. mauf. vs. service) | Refer to the text |
| $\sigma_2$ | 2 | ES (GV vs. EV) | Refer to the text |
| $\sigma_3$ | 4.2 | ES (EV models) | Barwick et al. (2024) |
| $\epsilon_k$ | | Income elasticity | |
| $k = a$: Auto | 1.4 | | Refer to the text |
| $k = m$: Manuf. | 1 | | Normalized |
| $k = s$: Service | 1.2 | | Refer to the text |
| $k = g$: GV | 1 | | Normalized |
| $k = e$: EV | 1.3 | | Refer to the text |
| *Production Parameters*, $\mathbb{F}$ | | | |
| $\alpha$ | 0.4 | Share of input (batteries) | Fixed |
| $\eta$ | 2.859 | ES (domestic vs. imported input) | Blaum et al. (2018) |
| $\kappa$ | 4 | ES (input variety) | Fixed |
| $\delta$ | 1.9 | Parameter in demand shifter<br>- related to consumer targeting | Nigai (2025) |
| $b$ | 0.001 | Shifter for consumer targeting cost | Nigai (2025) |
| $t_{ijb}$ | (0.02,0.04) | MFN Tariff on Batteries | WTO Integrated Database (IDB) |
| $\psi$ | (4.653,4.653) | Productivity dist.(shape, $\phi$) | IEA (2025) |
| $\theta$ | (7.3756,4.0802) | Productivity dist.(shape, $\omega$) | Automotive Manufacturing Solution |

$\mathbb{F}$ shows a set of production side parameters. The cost share of intermediate inputs is set as $\alpha = 0.4$ as widely known[14] The elasticity of substitution between domestic and imported inputs is fixed at $\eta = 2.859$. This value for the electric machinery sector (ISIC Rev3. 31) and is estimated by Blaum et al. (2018). $\kappa$ is set to 4. For the consumer targeting parameters, I follow Nigai (2025) to assign $\beta = 0.001, \delta = 1.9$ amd $b = 3$. Also, the data for the tariff on imported batteries, $t_{ijb}$, is based on MFN applied rate obtained from World Trade Organization.

For the c.d.f. of firm productivity in EV sector, $F(\phi)$ and battery sector, $M(\omega)$, I assume Pareto distribution with shape parameter, $\psi$ and $\theta$, respectively. One advantage of assuming Pareto distribution is that the feature is preserved for the firm size. The shape parameter in this case changes

[14]Battery costs account for around 30-45 percent of total production cost of light-duty electric vehicles as reported in Forbes (2023, Aug. 17), "China Has Perfectly Tangled The Battery Value Chain With Electric Vehicles - A Combo The U.S. And Europe Will Find Hard To Beat"

to $\frac{\psi}{\sigma_3-1}$ and $\frac{\theta}{\kappa-1}$ which enables direct matching to the data (Helpman et al., 2004). Data for the global EV sales and battery sales are obtained from IEA (2025) and Lithium-ion Battery Gigafactory Database published by Automotive Manufacturing Solutions (AMS). Using the unit sales of EVs for the U.S. and 13 countries combined, I calculate the standard deviation of sales across countries as $\psi = 4.653$. AMS data contains information about multinational battery firms' production facilities. I use the production kWh capacity of existing facilities in each country as a proxy for firm size and obtain $\theta_i = 7.37$ for *Home* and $\theta_i = 4.08$ for *Foreign*.

$$\mathbb{O} = \{L_i, N_{ie}, N_{ib}, A_{im}, A_{is}, A_{ig}, \tilde{\tau}_{ij}^{m}, \tilde{\tau}_{ij}^{g}\}$$

Other aggregate fundamentals are in the set $\mathbb{O}$. Data for the aggregate labor endowment $L_i$ is from Penn World Tables. I assume that the mass of firms are proportional to sectoral revenue share of the population. Sectoral revenue data is from OECD Input-Output (I-O) Table. Then, I estimate the structural gravity model to identify the total productivity parameter for manufacturing, services and gasoline vehicle sector and trade cost for manufacturing, GV and battery sector. Based on the OECD I-O Table for year 2011-2019, I estimate the disaggregated gravity model (Anderson and Van Wincoop, 2003; Yotov et al., 2016; Silva and Tenreyro, 2006):

$$X_{ij,t}^{k} = \exp\left(\xi_1^k FTA_{ij,t} + \xi_2^k EU_{ij,t} + \mu_{i,t}^{k} + \mu_{j,t}^{k} + \mu_{ij}^{k}\right)\epsilon_{ij,t}^{k} \tag{36}$$

where $FTA_{ij,t}$ and $EU_{ij,t}$ are dummy variables for bilateral free trade and European economic agreement. $\mu_{i,t}^k, \mu_{j,t}^k, \mu_{ij}^k$ capture the exporter-year-sector, importer-year-sector and pair-sector specific fixed effects. From the results, I recover the pair-year varying components and set it as $\tilde{\tau}_{ij,t}^{k} = \exp\left(\hat{\xi}_1^k FTA_{ij,t} + \hat{\xi}_2^k EU_{ij,t} + \hat{\mu}_{ij}^{k}\right)$. Then, it is regressed on gravity variables to obtain results as in Table 2.

$$\hat{\tilde{\tau}}_{ij,t}^{k} = \hat{\gamma}_{cons}^{k} + \hat{\gamma}_{dist}^{k}\log(dist_{ij}) + \hat{\gamma}_{contig}^{k} contig_{ij} + \hat{\gamma}_{lang}^{k} lang_{ij} + \hat{\gamma}_{fta}^{k} FTA_{ij,t} + \hat{\gamma_{eu}}^{k} EU_{ij,t} \tag{37}$$

$$\hat{A}_{i,t}^{k} = \exp(\hat{\mu}_{i,t}^{k})^{\frac{1}{1-\sigma_3}} \tag{38}$$

Table 2: Calibration Results for Trade Costs

| *Trade Cost* | Manufacturing | Gasoline Vehicle | Battery Input |
|---|---|---|---|
| log(Distance$_{ij}$), $\gamma_{dist}$ | 0.277 | 0.189 | 0.219 |
| | (0.009) | (0.013) | (0.011) |
| Contiguity$_{ij}$, $\gamma_{contig}$ | -0.008 | -0.111 | 0.001 |
| | (0.030) | (0.043) | (0.036) |
| Language$_{ij}$, $\gamma_{lang}$ | -0.343 | -0.114 | -0.388 |
| | (0.0237) | (0.035) | (0.026) |
| FTA$_{ij,t}$, $\gamma_{fta}$ | 0.084 | -0.304 | -0.005 |
| | (0.014) | (0.020) | (0.017) |
| EU$_{ij,t}$, $\gamma_{eu}$ | 0.027 | -0.041 | -0.055 |
| | (0.019) | (0.028) | (0.023) |
| Constant, $\gamma_{cons}$ | -0.911 | 0.173 | -0.314 |
| | (0.082) | (0.119) | (0.099) |
| Obsv. | 9,780 | 9,786 | 9,780 |

*Notes:* This table shows the parameters estimated for the trade cost in manufacturing sector, gasoline vehicle and battery industry (equation (37)). *Data source: WTO Input-Output Table*; Exporters include Austria, Belgium, France, Germany, Hungary, Italy, Poland, Spain, Slovakia, Sweden and United States. Importers include 80 countries. Years span 2012 - 2021, excluding 2020.

Based on the results, estimates of the trade cost $\hat{\hat{\tau}}^{k}_{ij,t}$ and productivity $\hat{A}_{ik}$ for sector $k$ can be obtained as in equation (37) and (38). Note that the trade cost for battery sector, it is $d_{ijb} = \hat{\hat{\tau}}^{b}_{ij,t}$. Also, I assume the productivity of non-tradable service sector is the same across two countries.

Now, the parameters left to be calibrated are $\{f_i^{im}, f_i^{I}, \gamma_{ie}\}$. I employ the following set of data: country-level sales share of EVs to GVs from IEA (IEA, 2025), firm-level average domestic input share in EV sector imputed with Bloomberg Supply Chain data and the total number of affiliates from origin to destination country in manufacturing (NAICS 33)[15] obtained from Ahmad et al. (2023). The objective of the calibration is to minimize the sum of the mean squared error between the model outcomes and corresponding data targets. I rely on brute-force method to find the local minimum and the resulting calibration fit is presented in Table 3.

### 5.2 Quantitative Results

In this section, I evaluate the effectiveness of demand-side industrial policy in achieving its objectives of creating quality manufacturing jobs and facilitating the energy transition for climate change mitigation. I benchmark the analysis on the U.S. Inflation Reduction Act to quantitatively examine

[15] NAICS 33 is one of three manufacturing code which includes metal, machinery, electric equipment, transportation etc.

Table 3: Targeted vs. Untargeted Moments

| | Targeted | | | | | | Untargeted |
|---|---|---|---|---|---|---|---|
| | Sales of EV to GV | | FDI share | | Average domestic input share | | Global EV market share |
| | $H$ | $F$ | $H \to F$ | $F \to H$ | $H$ | $F$ | $H$ |
| Data | 0.02 | 0.03 | 0.35 | 0.07 | 0.12 | 0.41 | 0.49 |
| Model | 0.03 | 0.03 | 0.36 | 0.07 | 0.11 | 0.40 | 0.39 |

*Notes:* In this table, $\{\gamma_{ie}, f_i^I, f_i^{im}\}$ are calibrated to match sales share of electric vehicles (EV) to gasoline vehicles, foreign direct investment share of NAICS 33 and EV firms' average domestic battery sourcing share. $H$ is *Home* calibrated to the U.S. and $F$ is *Foreign* calibrated to 13 developed countries: Austria, Belgium, Germany, Spain, France, United Kingdom, Hungary, Italy, Japan, South Korea, Poland, Slovakia, Sweden. The global EV market share is the U.S. EV sales share among the 12 countries and the U.S. combined.

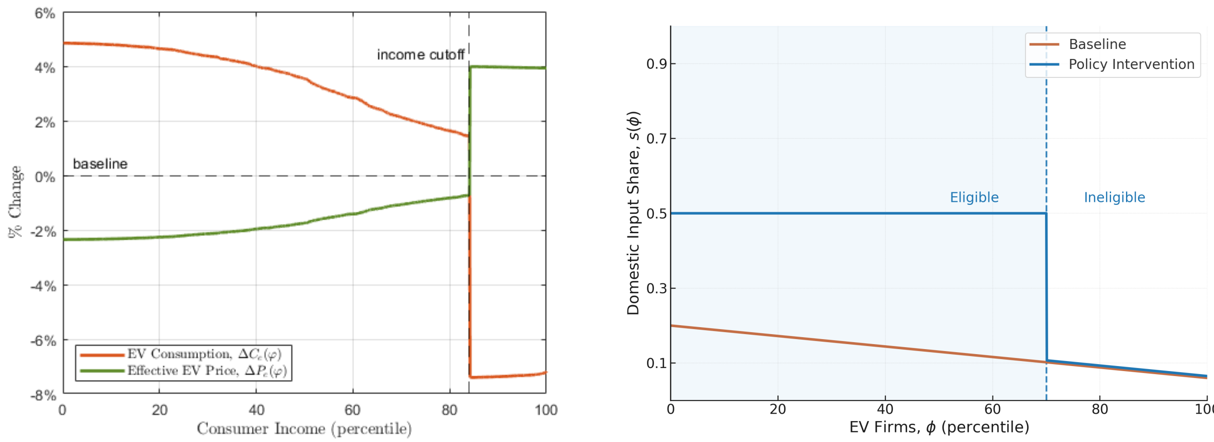
how the consumer subsidies for EV purchases subject to income cap and domestic input requirement affect FDI inflows into battery sector. I then measure the resulting changes in employment and aggregate EV sales. Next, I conduct two counterfactual experiments. First, I adjust one of the policy margins consistent with the IRA to illustrate how outcomes respond to alternative policy settings. Second, I compare these outcomes with those generated by a trade policy and emphasize the critical role of demand-side incentives in promoting FDI and sustaining the EV supply chain.

Throughout the analysis, the income cutoff for the subsidy is endogenously determined at the 84th percentile of income distribution, as defined in equation (33). This specification aligns with Borenstein and Davis (2016), who document the distributional effects of clean-energy tax credits. They find that the top quintile received about 60% of total credits, implying that the policy should target the bottom three quintiles for balanced adoption.

### 5.2.1 IRA Benchmark

As illustrated in section 2, I set the consumer subsidy rate $S = 25\%$ and the domestic input requirement $T = 50\%$ as a benchmark, consistent with the initial restriction of the IRA. In this setting, the consumer subsidy has a positive effect on attracting FDIs raising the share of foreign firms building facilities in the U.S. from 7.08% to 14.07%. Accordingly, the employment in the U.S. battery sector increases by 136%. However, the aggregate EV sales show a slight decrease of 2.25%.

Figure 6 shows how consumers and EV firms across income and productivity levels respond to the policy. In Panel A, eligible consumers below the income cutoff increase their EV purchases by 1-5% in response to the subsidy. The lower their income, the larger the increase in consumption, reflecting both the corresponding changes in the effective average prices and the high income elasticity of EV demand. In contrast, ineligible consumers, who face higher prices than before, reduce their purchases about 7%.




Panel A: EV Sales-Price Changes

Panel B: EV Firms' Domestic Input Share Changes

*Notes:* This figure illustrates how consumers and EV firms in the United States adjust their decisions under the benchmark policy. Panel A presents changes in average EV prices and sales across income groups. The subsidy's income cutoff is set at the 84th percentile. Sales increase among eligible consumers whose income is below the cutoff because the subsidy lowers their effective purchase price. Ineligible consumers with incomes above the cutoff reduce their EV purchases. Panel B depicts EV firms' adjustments in their domestic battery input shares following the policy: firms up to the 73rd productivity percentile comply by raising their domestic input share to 50%, the threshold specified by the policy.

Figure 6: Benchmark Changes in Decisions of Consumers and EV Firms

These price changes, which vary across consumer income levels, can be attributed to EV firms' endogenous decisions on whether to comply with the policy. Panel B of Figure 6 illustrates which firms choose to comply and how much they increase their domestic input shares. Following the introduction of the subsidy, firms up to 73rd productivity percentile raise their share of domestically produced batteries to meet the $T = 50\%$ threshold as demand for eligible EV models increases. This behavior has two implications. First, it raises the unit costs of models produced by eligible firms, since these firms shift their battery sourcing from more efficient suppliers in South Korea and Japan to less efficient producers in the United States. Because the extent of this shift is larger among more productive firms, the resulting unit cost increase is smaller for firms with lower productivity. Second, by choosing to produce eligible models, these firms reorient their product lines toward entry-level models that cater to lower-income consumers. Specifically, their target income percentile shifts from the 68th to the 53rd. On the other hand, firms that do not comply with the policy and maintain their previous share of imported inputs now target relatively higher-income consumers, with their target shifting from the 68th to the 73rd percentile.

The increase in unit production costs raises the average EV prices faced by all consumers, but the magnitude of this effect is heterogeneous, depending on the match between consumer tastes and firm's targeting. In other words, the prices of individual models are weighed differently when computing the average price each consumer faces. For instance, lower-income consumers, who have stronger preference for lower quality and entry-level models, place greater weight on price changes for low-productivity models, while price changes in high-end models have only a minor impact on their effective prices. This makes the price increase that lower-income consumers would have faced without the subsidy relatively small, since the unit cost increases for low-productivity firms are modest. Once the subsidy is applied, their effective prices fall by about 1-2% below the baseline level, as shown in Panel A. However, ineligible consumers who do not receive the subsidy face the full extent of the price increase of approximately 4%.

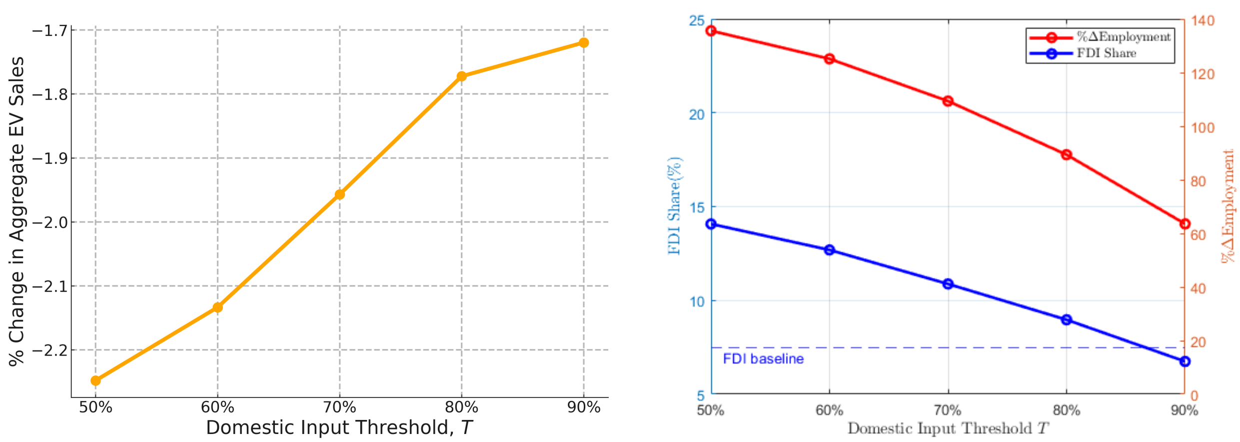
Consequently, these contrasting responses of eligible and ineligible consumers lead to a 2.25% decline in total EV sales. Although eligible consumers account for more than 80% of the population, the reduction in purchases among higher-income consumers dominates, as they held the majority of the market share prior to the policy. The policy, however, affects the battery sector in the opposite direction. Since both the sales of eligible models and their domestic input shares increase, the demand for domestically produced batteries rises. As a result, more foreign battery firms are incentivized to establish their production facilities in the United States, raising the share of firms undertaking FDI from 7.48% to 15.67%. In addition, incumbent producers expand their output to meet the higher demand. Accordingly, the employment in the battery sector increases by 136%.

#### 5.2.2 Counterfactual 1: IRA-Consistent Alternative Policy

Note that the IRA plans to increase the domestic input threshold $T$ by 10% every year until 2029. In this section, I follow the policy to increment the domestic input threshold $T$ by 10% from 50% to 90% and analyze how the outcomes change.

Consumption responses evolve differently across income groups as the threshold rises. As the threshold increases, eligible consumers diminish whereas ineligible consumers expand their purchases, as depicted in Figure E3 in Appendix Appendix E. In this counterfactual setting, eligible consumers adopt more EVs than the pre-policy baseline only when $T$ ranges between 50–70%. At $T = 60\%$ and $T = 70\%$, consumption rises modestly by 0–3% and 0–2%, respectively. Beyond this range, the subsidy becomes insufficient to offset the price increase, reducing consumption below the baseline. Among ineligible consumers, adoption rises gradually from -7% to -3% as the threshold increases.

To understand the heterogeneous consumption patterns, it is essential to examine how prices vary across thresholds. Two countervailing margins of firm behavior interact along the thresholds to determine the average price of EV models. One is whether to meet the eligibility criteria $T$ (extensive margin) and the other is how much share of input sourcing is shifted to the domestic market (intensive margin). When the threshold $T$ increases, the number of firms complying to the eligibility condition shrinks while their domestic input shares increase.[16] The latter contributes to the price increases through unit cost rise, whereas the former leads to price drop as the firms deviate from meeting high $T$ and return to their original lower share of domestic sourcing.




Panel A: Aggregate EV Sales Change

Panel B: FDI Share and Employment Changes

*Notes:* This figure presents changes in aggregate EV sales, FDI share, and corresponding employment in the U.S. battery sector across domestic input thresholds ($T$) ranging from 50% to 90%. Panel A shows an upward trend in EV sales, though the change remains negative across all thresholds. In contrast, Panel B depicts a downward trend in both the FDI share and employment as $T$ increases.

Figure 7: Across-Policy Changes Compared to Baseline

[16] Refer to Figure E4 in Appendix E.

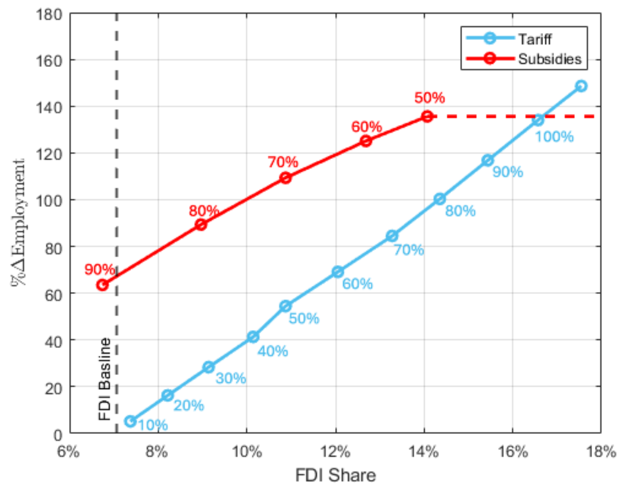
As illustrated in the benchmark policy analysis, the average effective price faced by each consumer depends on the interaction between those two countervailing margins and on which segment of firms each consumer places greater weight in their consumption basket. Suppose the domestic input threshold $T$ is raised from 50% to 60%. In that case, the share of EV firms choosing to produce eligible models are declines from 73% to 65%, with the more productive firms being the first to deviate. This implies that roughly 8% of more productive firms reduce their domestic input shares back to pre-policy levels, while remaining 65% increase theirs by 10%. In response to these changes, lower-income consumers receiving the subsidy face higher average prices, as they weigh more on relatively lower quality products that better match their preferences. In other words, the upward price pressure from higher domestic input shares among eligible firms outweighs the downward pressure from firms opting out of compliance and reverting to their pre-policy sourcing patterns. Conversely, the downward pressure is stronger for the higher-income consumers who are ineligible for the subsidy, leading to lower prices they face. As a result, prices continue to rise for eligible consumers and decline for ineligible ones as the threshold increases up to $T = 90\%$.

This patterns generate two contrasting effects on the EV and battery sectors. First, aggregate EV sales decline overall but the magnitude of the decrease lessens as $T$ increases. Panel A in Figure 7 shows that the sales fall by 2.25% at $T = 50\%$, narrowing to a 1.72% decline at $T = 90\%$ relative to the baseline. Second, the share of foreign battery firms' FDI in the U.S. decreases with higher $T$. As demand from eligible consumers rises, so does the demand for domestically produced batteries. In Panel B of Figure 7, the FDI share peaks at 14% when $T = 50\%$, where eligible consumer sales are also highest, and then steadily falls to 6% at $T = 90\%$. Together with the expansion of domestic production by incumbent U.S. firms and higher FDI share, the employment rises substantially but tapers off from 136% to 64%.

#### 5.2.3 Counterfactual 2: Comparison with Trade Policy; IRA Subsidy vs. Import Tariff

As the second counterfactual experiment, I compare the effectiveness of the IRA in attracting FDIs to one of frequently used trade policies: import tariff. The rationale for tariff is different from the IRA in that it only intervenes on the supply side and attract FDIs by increasing the cost of trade. Compared to the IRA, it's more direct and rather punishing whereas the IRA indirectly encourages

FDIs by providing incentives. It turns out that import tariff does draw positive share of FDIs but it is slower in growing the battery industry and costlier than the IRA.




*Notes:* This figure compares employment changes under two policy scenarios—the IRA consumer subsidy and an import tariff—given the corresponding FDI share induced by each policy. The percentage labels along the graphs indicate the specific policy rates. It shows that the subsidies are more effective in generating employment for a given level of FDI share.

Figure 8: Comparison between IRA Subsidy vs. Import Tariff

To show, I run counterfactual simulations under import tariff where the ad-valorem rate ranges from 10% to 100%. Figure 8 reports the employment increase in the battery industry given FDI share under each policy. The percentages near the graphs indicate the rate of each policy. In the graph, increasing tariff rate induces higher FDI share and employment. However, the extent of FDI increase leading to the rise of employment is limited in comparison to the IRA. For instance, given 14% of foreign firms building facilities in the U.S., the IRA subsidy creates 136% more jobs but tariff can only result in create less than 100% increase. Also, to replicate the maximum employment achieved under the IRA, tariff should be set higher than 100%.

Though inefficient, tariff does affect the battery firms positively. However, this entails a large cost. The EV sales fall by 2.5% per every 10% increase in tariff. When the tariff rate reaches 100%, the total EV sales drop amounts to 27% and this occurs throughout the income distribution. This means that tariff is undermining the EV sector in return to the FDI increase in the battery industry. Since these two sectors are highly complementary, it would harm the entire supply chain if this effect persists. In fact, the employment along the supply chain constantly decreases up to 6.9%.

However, the employment for the EV supply chain always increases up to 5% under the IRA. The difference between these two policy results emphasizes the importance of inducing demand in industrial transition and growth.

## 6 Conclusion

As demand-side industrial policy has become a common tool for developing green industries, creating good jobs, and mitigating climate change, the need to assess its effectiveness has grown. This paper provides the first quantitative evaluation of such a policy by benchmarking the U.S. Inflation Reduction Act. I focus on the mechanism through which EV purchase subsidies, conditional on an income cap and a domestic content requirement, induce FDI by battery firms, a key input to EVs. Using a two-country general-equilibrium trade model with income-heterogeneous consumers, I show that the rise in the EV purchases from lower-income, subsidy-eligible consumers drives FDI inflows as well as battery-sector employment. On the other hand, a drop in sales from higher-income, ineligible consumers reduce aggregate EV adoption.

I also conduct two counterfactual experiments that highlights the importance of demand-side incentive in driving FDIs. First, when the minimum domestic input threshold for eligibility is tightened, the FDI share falls and employment declines, as the policy becomes less favorable to lower-income consumers and workers. At the same time, EV adoption rises slightly as higher-income consumers increase their purchases. Second, comparing the IRA with an import tariff, I find that tariffs are more costly for achieving a given amount of FDI and less efficient at converting FDI into employment gains.

# References

S. Ahmad, J. Bergstrand, J. Paniagua, and H. Wickramarachi. The multinational revenue, employment, and investment database (mreid). *USITC Economics Working Paper*, 11-B, 2023. URL https://doi.org/10.71894/wjf6-ra65.

J. Ahn, B. Carton, A. Habib, D. Malacrino, D. Muir, and A. Presbitero. Geoeconomic fragmentation and foreign direct investment. *International Monetary Fund*, 4, 2023.

K. Aiginger and D. Rodrik. Rebirth of industrial policy and an agenda for the twenty-first century. *Journal of industry, competition and trade*, 20:189–207, 2020.

S. Aiyar, D. Malacrino, and A.F. Presbitero. Investing in friends: The role of geopolitical alignment in fdi flows. *European Journal of Political Economy*, 83:102508, 2024.

L. Alfaro and D. Chor. Global supply chains: The looming "great reallocation". *National Bureau of Economic Research*, (w31661), 2023.

H. Allcott and Maydanchik M.S. Kane, R. The effects of "buy american": Electric vehicles and the inflation reduction act. *National Bureau of Economic Research*, (w33032), 2024.

J.E. Anderson and E. Van Wincoop. Gravity with gravitas: A solution to the border puzzle. *American economic review*, 93(1):170–192, 2003.

P. Antras, T.C. Fort, and F. Tintelnot. The margins of global sourcing: Theory and evidence from us firms. *American Economic Review*, 107(9):2514–2564, 2017.

P. Antràs, A. De Gortari, and O. Itskhoki. Globalization, inequality and welfare. *Journal of International Economics*, 108:387–412, 2017.

O. Attanasio, K. Larkin, M.O. Ravn, and M. Padula. (s) cars and the great recession. *Econometrica*, 90(5):2319–2356, 2022.

P.J. Barwick, H.S. Kwon, and S. Li. Attribute-based subsidies and market power: an application to electric vehicles. *National Bureau of Economic Research*, (w32264), 2024.

R. Benabou. Tax and education policy in a heterogeneous-agent economy: What levels of redistribution maximize growth and efficiency? *Econometrica*, 70(2):481–517, 2002.

J. Blaum, C. Lelarge, and M. Peters. The gains from input trade with heterogeneous importers. *American Economic Journal: Macroeconomics*, 10(4):77–127, 2018.

S. Borenstein and L.W. Davis. The distributional effects of us clean energy tax credits. *Tax Policy and the Economy*, 30(1):191–234, 2016.

C.P. Bown. Modern industrial policy and the world trade organization. *Annual Review of Economics*, 16, 2024.

S.L. Brainard. An empirical assessment of the proximity-concentration trade-off between multinational sales and trade. *The American Economic Review*, 87(4):520–44, 1997.

J. Caron, T. Fally, and J.R. Markusen. International trade puzzles: A solution linking production and preferences. *The Quarterly Journal of Economics*, 129(3):1501–1552, 2014.

D.L. Carr, J.R. Markusen, and K.E. Maskus. Estimating the knowledge-capital model of the multinational enterprise. *American Economic Review*, 91(3):693–708, 2001.

T. Chaney. Distorted gravity: the intensive and extensive margins of international trade. *American Economic Review*, 98(4):1707–1721, 2008.

D. Comin, D. Lashkari, and M. Mestieri. Structural change with long-run income and price effects. *Econometrica*, 89(1):311–374, 2021.

C. Criscuolo, N. Gonne, K Kitazawa, and G. Lalanne. An industrial policy framework for oecd countries: Old debates, new perspectives. *OECD Science, Technology and Industry Policy Papers, OECD Publishing, Paris*, (127), 2022a.

C. Criscuolo, N. Gonne, K Kitazawa, and G. Lalanne. Are industrial policy instruments effective?: A review of the evidence in oecd countries. *OECD Science, Technology and Industry Policy Papers, OECD Publishing, Paris*, (128), 2022b.

G. Duernecker, B. Herrendorf, and A. Valentinyi. Structural change within the services sector and the future of cost disease. *Journal of the European Economic Association*, 22(1):428–473, 2024.

S. Evenett, A. Jakubik, F. Martín, and M. Ruta. The return of industrial policy in data. *The World Economy*, 47(7):2762–2788, 2024.

P. Fajgelbaum, G.M. Grossman, and E. Helpman. A linder hypothesis for foreign direct investment. *he Review of Economic Studies*, 82(1):83–121, 2015.

K.T. Gillingham, A.A. van Benthem, S. Weber, M.A. Saafi, and X. He. Has consumer acceptance of electric vehicles been increasing? evidence from microdata on every new vehicle sale in the united states. *AEA Papers and Proceedings*, 113:329–335, 2023.

R. Goldberg, P.K.and Juhász, N.J. Lane, G.L. Forte, and J. Thurk. Industrial policy in the global semiconductor sector. *National Bureau of Economic Research*, (w32651), 2024.

K. Head and T. Mayer. Market potential and the location of japanese investment in the european union. *Review of Economics and Statistics*, 86(4):959–972, 2004.

K. Head, T. Mayer, M. Melitz, and C. Yang. Industrial policies for multi-stage production: The battle for battery-powered vehicles. *Tech. rep., Mimeo.*, 74, 2024.

J. Heathcote, K Storesletten, and G.L. Violante. Optimal tax progressivity: An analytical framework. *The Quarterly Journal of Economics*, 132(4):1693–1754, 2017.

E. Helpman, M.J. Melitz, and S.R. Yeaple. Export versus fdi with heterogeneous firms. *American economic review*, 94(1):300–316, 2004.

J. Horowitz, D. Coffin, and B. Taylor. Supply chain for ev batteries: 2020 trade and value-added update. *U.S. International Trade Commission*, ID-21-072, 2021.

D. Hummels and K.Y. Lee. The income elasticity of import demand: Micro evidence and an application. *Journal of international Economics*, 113:20–34, 2018.

IEA. Global supply chains of ev batteries. *International Energy Agency*, https://www.iea.org/reports/global-supply-chains-of-ev-batteries(4):77–127, 2022.

IEA. Global electric vehicle outlook 2025. *International Energy Agency*, 2025. URL `https://www.iea.org/reports/global-ev-outlook-2025`.

J. Ju, H. Ma, Z. Wang, and X. Zhu. Trade wars and industrial policy competitions: Understanding the us-china economic conflicts. *Journal of Monetary Economics*, 141:42–58, 2024.

R. Juhász and N. Lane. The political economy of industrial policy. *Journal of Economic Perspectives*, 38(4):27–54, 2024.

R. Juhász, N. Lane, and D. Rodrik. The new economics of industrial policy. *Annual Review of Economics*, 16, 2023.

S. Li, X. Zhu, Y. Ma, F. Zhang, and H. Zhou. The role of government in the market for electric vehicles: Evidence from china. *Journal of Policy Analysis and Management*, 41(2):450–485, 2022.

J. Linn and C. Shen. The effect of income on vehicle demand: Evidence from china's new vehicle market. *Journal of the Association of Environmental and Resource Economists*, 11(1):41–73, 2024.

S. Lui, R. Riley, D. Holland, A. Orazgani, and P. Paluchowski. Long run income elasticities of import demand. *BIS Research Paper*, 144, 2013.

J.R. Markusen. Multinationals, multi-plant economies, and the gains from trade. *Journal of International Economics*, 15(3-4):205–226, 1984.

J.R. Markusen. Multinational firms and the theory of international trade. *MIT Press*, 2002.

J.R. Markusen and K.E. Maskus. Discriminating among alternative theories of the multinational enterprise. *Review of international economics*, 10(4):694–707, 2002.

P.S. McCarthy. Market price and income elasticities of new vehicle demands. *The Review of Economics and Statistics*, pages 543–547, 1996.

M.J. Melitz. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725, 2003.

E. Muehlegger and D.S. Rapson. Subsidizing low-and middle-income adoption of electric vehicles: Quasi-experimental evidence from california. *Journal of Public Economics*, 216:104752, 2022.

E. Muehlegger and D.S. Rapson. The economics of electric vehicles. *Review of Environmental Economics and Policy*, 17(2):274–294, 2023.

S. Nigai. International transmission of inequality through trade. *American Economic Journal: Economic Policy*, 17(3):311–44, 2025.

OECD. Oecd inter-country input-output tables.

J.S. Silva and S. Tenreyro. The log of gravity. *The Review of Economics and statistics*, pages 641–658, 2006.

P. Slowik, S. Searle, H. Basma, J. Miller, Y. Zhou, F. Rodríguez, C. Buysse, S. Kelly, R. Minjares, L. Pierce, and R. Orvis. Analyzing the impact of the inflation reduction act on electric vehicle uptake in the united states. *International Council on Clean Transportation*, 2023.

K. Springel. Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives. *American Economic Journal: Economic Policy*, 13(4):393–432, 2021.

L. Vanhaverbeke, D. Verbist, G. Barrera, M. Csukas, and R. Jüriado. Consumer monitor 2023 european alternative fuels observatory eu aggregated report. *European Commission*, (MI-05-24-449-EN-N), 2023.

White House. Building a clean energy economy: A guidebook to the inflation reduction act's investments in clean energy and climate action. *The White House*, 2023.

S.R. Yeaple. Firm heterogeneity and the structure of us multinational activity. *Journal of International Economics*, 78(2):206–215, 2009.

K.M. Yi. Can multistage production explain the home bias in trade? *American Economic Review*, 100(1):364–393, 2010.

Y.V. Yotov, R. Piermartini, and M. Larch. An advanced guide to trade policy analysis: The structural gravity model. *United Nations and World Trade Organization*, 2016.

# Appendix A Background

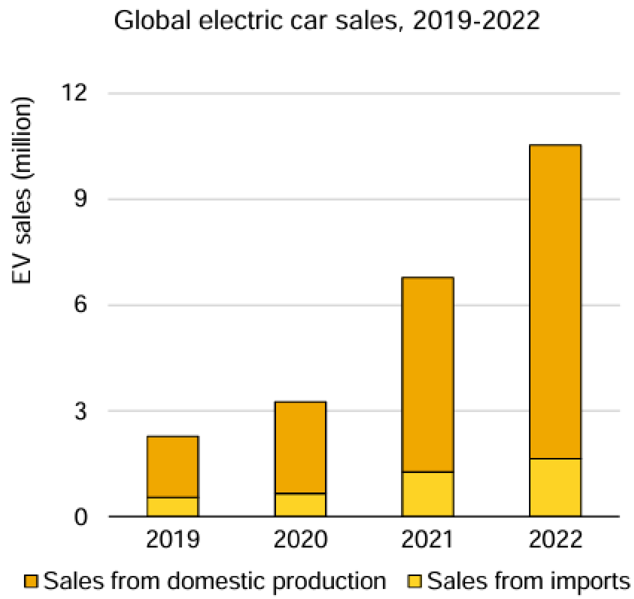
## A.1 Supplemental Results

Table A1: EV Sales by Country (thousand units)

| Country | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 |
|---|---|---|---|---|---|---|
| China | 830 | 920 | 2,700 | 4,400 | 5,400 | 6,400 |
| USA | 240 | 230 | 470 | 800 | 1,100 | 1,200 |
| Austria | 9.3 | 16 | 33 | 34 | 48 | 45 |
| Belgium | 8.8 | 15 | 23 | 38 | 93 | 130 |
| France | 45 | 110 | 170 | 210 | 310 | 300 |
| Germany | 63 | 190 | 360 | 470 | 520 | 380 |
| Hungary | 1.8 | 3.0 | 4.3 | 4.7 | 5.8 | 8.6 |
| Italy | 11 | 33 | 67 | 49 | 66 | 66 |
| Japan | 21 | 15 | 22 | 59 | 88 | 60 |
| Korea | 33 | 31 | 72 | 120 | 120 | 120 |
| Sweden | 16 | 28 | 57 | 96 | 110 | 94 |
| United Kingdom | 38 | 110 | 190 | 270 | 310 | 380 |
| Poland | 1.5 | 3.7 | 7.2 | 14 | 17 | 17 |
| Slovakia | 0.16 | 0.92 | 1.1 | 1.4 | 2.3 | 2.2 |
| Spain | 10 | 18 | 24 | 33 | 57 | 62 |

Table A2: EV Price Premium and Average Transaction Prices

| | 2019 | 2020 | 2021 | 2022 | 2024 |
|---|---|---|---|---|---|
| Price premium for EVs (%) | 50 | 16 | 26 | 36 | 15 |
| Electric vehicle average (USD) | 56,239 | 44,704 | 54,139 | 64,932 | 55,845 |
| Industry average (USD) | 37,462 | 38,399 | 43,104 | 47,598 | 48,531 |



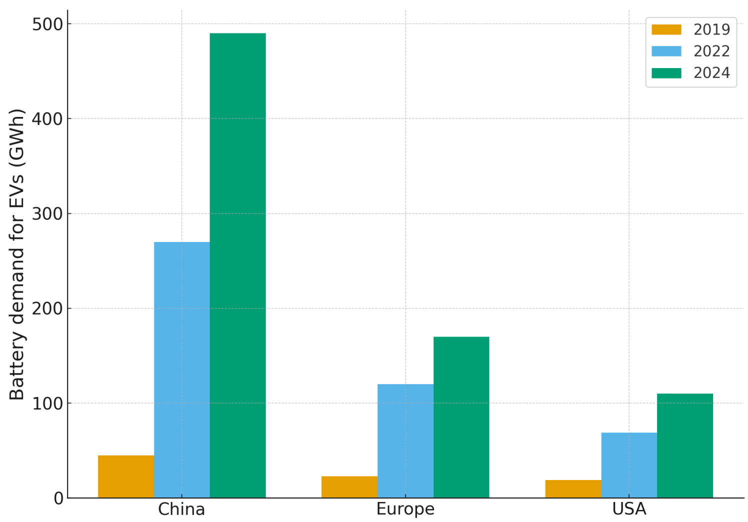

*Source:* *IEA Global EV Outlook 2023*. This figure reports the approximate share of domestically produced electric vehicle models among all those sold in the world. More than 75% of cars are produced and sold domestically.

Figure A1: Global Electric Car Sales, 2019-2022

Table A3: Residual Relative Log Consumption Share on Residual Aggregate Consumption

| Dependent Variable: | $\log\left(\frac{\text{Electric Vehicle}}{\text{Gasoline Vehicle}}\right)$ | |
|---|---|---|
| *Residual Log Real Consumption* | (1) | (2) |
| *Residual Log Real Income* | 8.41 | 8.34 |
| | (0.41) | (0.40) |
| State FE | Y | Y |
| County Controls | N | Y |
| $R^2$ | 0.24 | 0.22 |
| Observations | 2172 | 2172 |

*Note:* Standard errors clustered by county. Residual log real income is constructed by taking residuals of the following OLS regression: $\log(C_{cst}) = \xi_s + X_{cst} + \epsilon_{cst}$ where subscript $c$ is county, $s$ is state and $t$ is year. $\xi_s$ denotes the state fixed effects and $\epsilon_{cst}$ denotes the error term. $X_{cst}$ denotes county-level controls which include metro dummy, average age, education level, and ratio of sex. Residual log real electric vehicle consumption relative to gasoline vehicle consumption is constructed in a similar manner.




*Source:* *IEA Global EV Outlook 2025*. This figure reports the increasing battery demand from each region from 2019 to 2024. China has the largest demand throughout the years followed by Europe and United States.

Figure A2: Battery Demand By Region

# Appendix B Model

## B.1 Detailed Derivation 1 for section 3.3

Assume that the productivity of battery producers are distributed as Pareto with shape parameter $\theta$, in which the cumulative density function is $M_j(\omega)$. Then, the share of foreign battery varieties that an EV firm $\phi_i$ in country $i$ sources from $j$ is,

$$\begin{aligned} 1 - M_j(\bar{\omega}_j(\phi_i)) &= Pr(\omega \geq \bar{\omega}_j(\phi_i)) \\ &= \big(\omega_{j,min}/\bar{\omega}_j(\phi_i)\big)^{\theta} = n(\phi_i) \end{aligned} \tag{39}$$

Also, note that $\omega_j^I$ is the cutoff productivity of battery firms in country $j$. The price index for the imported composite batteries are

$$\begin{aligned} A(\Omega_j(\phi))^{1-\kappa} &= \int_{\Omega_j(\phi)} \Big[\frac{\kappa}{\kappa-1}\frac{w_j\tau_{ji}}{\omega}\Big]^{1-\kappa} d\omega \\ &= \Big(\frac{\kappa}{\kappa-1} w_j \tau_{ji}\Big)^{1-\kappa} N_{jb} \int_{\bar{\omega}(\phi)}^{\omega^I} \omega^{\kappa-1} dM(\omega) \end{aligned}$$

where $dM(\omega) = \theta \cdot \omega_{\min}^{\theta} \omega^{-\theta-1}$. Then,

$$A(\bar{\omega}_j(\phi))^{1-\kappa} = \Big(\frac{\kappa}{\kappa-1} w_j \tau_{ji}\Big)^{1-\kappa} \frac{N_{jb}\theta}{\theta-\kappa+1} \omega_{\min}^{\theta} \Big[\big(\omega^I\big)^{-\theta+\kappa-1} - \big(\bar{\omega}_j(\phi_i)\big)^{-\theta+\kappa-1}\Big]$$

Plugging in equation 39 in the above equation,

$$\begin{aligned} A\big(n(\phi_i)\big) &= \underbrace{\omega_{j,\min}^{-1}\Big(\frac{N_{jb}\theta}{\theta-(\kappa-1)}\Big)^{\frac{1}{1-\kappa}} \frac{\kappa}{\kappa-1} w_j \tau_{ji}}_{\equiv a_{ji}} \Big[n(\phi)^{1+\frac{1-\kappa}{\theta}} - (n^{I*})^{1+\frac{1-\kappa}{\theta}}\Big]^{\frac{1}{1-\kappa}} \\ &= a_{ji} \cdot \Big[n(\phi_i)^{1+\frac{1-\kappa}{\theta}} - (n^{I*})^{1+\frac{1-\kappa}{\theta}}\Big]^{\frac{1}{1-\kappa}} \end{aligned}$$

### B.2 Detailed Derivation 2 for section 3.3

$$\begin{aligned} SC\big(n(\phi)\big) &= n(\phi)^{1+\frac{1-\kappa}{\theta}} - (n^{I*})^{1+\frac{1-\kappa}{\theta}} \\ &\underset{eq.(13)}{=} A\big(n(\phi)\big)^{1-\kappa} a^{\kappa-1} \end{aligned}$$

To obtain $A\big(n(\phi)\big)$ as a function of $s(\phi)$, modify the equation (14) as

$$\begin{aligned} s(\phi)^{-1} &= \frac{q^{1-\eta}}{q^{1-\eta} + A\big(n(\phi)\big)^{1-\eta}} \\ &= 1 + q^{\eta-1} A\big(n(\phi)\big)^{1-\eta} \end{aligned}$$

Then, $A\big(n(\phi)\big)$ can be written as

$$A\big(\phi\big)^{1-\kappa} = \Big(\frac{1-s(\phi)}{s(\phi)}\Big)^{\frac{1-\kappa}{1-\eta}} q^{1-\kappa}$$

# Appendix C Solution Algorithm

I approximate income distribution $H_i(\varphi)$ and productivity distributions, $F_i(\phi), M_i(\omega)$ as vectors of $1000 \times 1$ size. Given the primitives of two countries - home and foreign - the equilibrium satisfies equations in $(i) - (xxix)$. The solution algorithm is based on the contraction mapping method which runs until it reaches a fixed point.

**[Taxation & Consumers]**

$$(i)\ \ \tilde{y} = \left( \frac{\int_\varphi y_i(\varphi) dH_i(\varphi) - G_i/L_i}{\int_\varphi y_i(\varphi)^{1-\rho} dH_i(\varphi)} \right)^{1/\rho}$$

$$(ii)\ \ y_i^d(\varphi) = y_i(\varphi)^{1-\rho} (\tilde{y}_i)^\rho$$

$$(iii)\ \ u_i(\varphi) = y_i^d(\varphi)/P_i(\varphi)$$

$$(iv)\ \ c_{ie}(\varphi) = \gamma_e \Big( \frac{P_{ie}(\varphi)}{P_{ia}(\varphi)} \Big)^{-\sigma_2} \Big( \frac{P_{ia}(\varphi)}{P_i(\varphi)} \Big)^{-\sigma_1} u_i(\varphi)^{\epsilon_e + \epsilon_a - 1}$$

$$(v)\ \ v(x_i(\phi)) = \int_\varphi \Big( 1 + \delta_i (f_i(\varphi) - x_i(\phi))^2 \Big)^{-1} P_{ie}(\varphi)^{\sigma_3} c_{ie}(\varphi) dH_i(\varphi)$$

**[EV Producers]**

$$(vi)\ \ \pi_{ie}(\phi_i, s_i(\phi), x_i(\phi); a_{ji}) = \frac{L_i}{\sigma_3} \Big( \frac{\sigma_3}{\sigma_3 - 1} w_i^{1-\alpha} q_i^\alpha \Big)^{1-\sigma_3} \phi^{\sigma_3 - 1} s_i(\phi)^{\frac{\alpha(1-\sigma_3)}{\eta - 1}} v(x_i(\phi))$$
$$- w_i f_i^{im} \Big( \frac{1 - s_i(\phi)}{s_i(\phi)} \Big)^{\frac{1-\kappa}{1-\eta}} \Big( \frac{q_i}{a_{ji}} \Big)^{1-\kappa} - b \cdot x_i(\phi)^\beta$$

where $a_{ji} = \omega_{j,\min}^{-1} \Big( \frac{N_{jb}\theta}{\theta - (\kappa - 1)} \Big)^{\frac{1}{1-\kappa}} \frac{\kappa}{\kappa - 1} w_j \tau_{ji}$

$$(vii)\ \ \{s_i^*(\phi), x_i^*(\phi)\} = \underset{s_i(\phi), x_i(\phi)}{\arg\max} \ \Big\{ \pi_{ie}\big(\phi_i, s_i(\phi), x_i(\phi); a_{ji}\big) \Big\}$$

$$(viii)\ \ \pi_{ie}^*(\phi_i, s_i^*(\phi), x_i^*(\phi); a_{ji}) = \frac{L_i}{\sigma_3} \Big( \frac{\sigma_3}{\sigma_3 - 1} w_i^{1-\alpha} q_i^\alpha \Big)^{1-\sigma_3} \phi^{\sigma_3 - 1} s_i^*(\phi)^{\frac{\alpha(1-\sigma_3)}{\eta - 1}} v_i(x^*(\phi))$$
$$- w_i f_i^{im} \Big( \frac{1 - s_i^*(\phi)}{s_i^*(\phi)} \Big)^{\frac{1-\kappa}{1-\eta}} \Big( \frac{q_i}{a_j i} \Big)^{1-\kappa} - b \cdot x_i^*(\phi)^\beta$$

$$(ix)\ \ X_{ie}^*(\phi) = L_i \Big( \frac{\sigma_3}{\sigma_3 - 1} w_i^{1-\alpha} q_i^\alpha \Big)^{1-\sigma_3} \phi^{\sigma_3 - 1} s_i^*(\phi)^{\frac{\alpha(1-\sigma_3)}{\eta - 1}} v(x_i^*(\phi))$$

**[Battery Producers]**

$$(x)\ \ \Phi_j(\omega_i) = \Big\{\phi_j | \omega_i \in \Omega(\phi_j)\Big\} \text{ where } \begin{cases} \Omega(\phi_j) = \{\omega_i | \omega_i \geq \bar{\omega}_i(\phi_j)\} \\ \bar{\omega}_i(\phi_j) = \Big[n^I(\phi_j)^{1+\frac{1-\kappa}{\theta}} + \Big(\frac{1-s_j^*(\phi)}{s_j^*(\phi)}\Big)^{\frac{1-\kappa}{1-\eta}} (q_j/a_{ij})^{1-\kappa}\Big]^{\frac{1}{-\theta-(1-\kappa)}} \omega_{i,min} \end{cases}$$

$$(xi) \begin{cases} DD_i = N_{ie} \int_{\phi_i} q_i^{\kappa-1} s_i^*(\phi) \Big(\alpha \dfrac{\sigma_3 - 1}{\sigma_3} X_{ie}^*(\phi)\Big) dF_i(\phi) \\ DX_{ij}(\omega_i) = N_{je} \int_{\phi_j \in \Phi_j^X(\omega_i)} \big(1 - s_j^*(\phi)\big)^{\frac{\kappa-\eta}{1-\eta}} s_j^*(\phi)^{\frac{\kappa-1}{\eta-1}} q_j^{\kappa-1} \Big(\alpha \dfrac{\sigma_3 - 1}{\sigma_3} X_{je}^*(\phi)\Big) dF_j(\phi) \end{cases}$$

$$(xii)\ \ \pi_{ib}^D(\omega_i) = \omega_i^{\kappa-1} \cdot \frac{1}{\kappa}\Big(\frac{\kappa}{\kappa-1}\Big)^{1-\kappa} w_i^{1-\kappa} DD_i$$

$$(xiii)\ \ \pi_{ijb}^X(\omega_i) = \omega_i^{\kappa-1} \cdot \frac{1}{\kappa}\Big(\frac{\kappa}{\kappa-1}\Big)^{1-\kappa} (w_i \tilde{\tau}_{ijb})^{1-\kappa} DX_{ij}(\omega_i), \quad \text{where } \tilde{\tau}_{ijb} = (1+\tau_{ijb}) t_{ijb}$$

$$(xiv)\ \ \pi_{ijb}^I(\omega_i) = \omega_i^{\kappa-1} \cdot \frac{1}{\kappa}\Big(\frac{\kappa}{\kappa-1}\Big)^{1-\kappa} w_j^{1-\kappa} DD_j - w_j f_j^I$$

$$(xv)\ \ \begin{cases} \omega_i^{X*} = \{\omega_i | \pi_{ijb}^X(\omega_i) > \pi_{ijb}^I(\omega_i)\} \\ \omega_i^{I*} = \{\omega_i | \pi_{ijb}^X(\omega_i) \leq \pi_{ijb}^I(\omega_i)\} \end{cases}$$

$$(xvi)\ \ n^{I*}(\phi_j) = \int_{\omega_i^{I*} \cap \Omega(\phi_j)} dM_i(\omega)$$

**[Aggregates]**

$$(xvii)\ \ \Pi_{ie} = N_{ie} \int_{\phi} \pi_{ie}^*(\phi_i, s_i^*(\phi), x_i^*(\phi); a_{ji}) dF_i(\phi)$$

$$(xviii)\ \ \Pi_{ib} = N_{ib}\Big(\int_{\omega} \pi_i^D(\omega_i) dM_i(\omega) + \int_{\omega_i \in \omega_i^X} \pi_{ij}^X(\omega_i) dM_i(\omega)\Big) + \int_{\omega_i \in \omega_i^I} \pi_{ij}^I(\omega_i) dM_i(\omega)\Big)$$

$$(xix)\ \ \frac{X_{ijb}}{1+t_{ijb}} = \begin{cases} N_{ie} \int_{\phi} s_i^*(\phi) \Big(\alpha \dfrac{\sigma_3 - 1}{\sigma_3} X_{ie}^*(\phi)\Big) dF_i(\phi) & \text{if } j = i \\ \frac{N_{je}}{1+t_{ijb}} \int_{\phi} \big(1 - s_j^*(\phi)\big) \Big(\alpha \dfrac{\sigma_3 - 1}{\sigma_3} X_{je}^*(\phi)\Big) dF_j(\phi) & \text{if } j \neq i \end{cases}$$

$$(xx) \begin{cases} dd_i = \frac{1}{L_i}\big(\Pi_{ie} + \Pi_{ib}\big) \\ tt_i = \frac{1}{L_i} t_{ijb} \frac{X_{ijb}}{1+t_{ijb}} \end{cases}$$

$$(xxi)\ \ y_i(\varphi) = l_i(\varphi) w_i + dd_i + tt_i$$

$(xxii)$ Regenerate $(i) - (v)$ and renew $v(x_i^*(\phi))$

$$(xxiii)\;\; q_i = \frac{\kappa}{\kappa-1} w_i \left[ N_{ib} \int_{\omega_i} \omega^{\kappa-1} dM_i(\omega) + N_{jb} \int_{\omega_j^{I*}} \omega^{\kappa-1} dM_j(\omega) \right]^{\frac{1}{1-\kappa}}$$

$$(xxiv)\;\; P_{ie}(\varphi)^{1-\sigma_3} = N_{ie} \Big( \frac{\sigma_3}{\sigma_3 - 1} w_i^{1-\alpha} q_i^{\alpha} \Big)^{1-\sigma_3} \int_{\phi_i^*} [1 + \delta(f_i(\varphi) - x_i^*(\phi))^2]^{-1} \times s_i^*(\phi)^{\frac{\alpha(1-\sigma_3)}{\eta-1}} \phi^{\sigma_3 - 1} dF_i(\phi)$$

$$(xxv) \begin{cases} P_{im} = \Big( \big(\frac{w_i}{A_{im}}\big)^{1-\sigma_2} + \big(\frac{w_j \tilde{\tau}_{jim}}{A_{jm}}\big)^{1-\sigma_2} \Big)^{\frac{1}{1-\sigma_2}} \\ P_{is} = \frac{w_i}{A_{is}} \\ P_{ig} = \Big( \big(\frac{w_i}{A_{ig}}\big)^{1-\sigma_3} + \big(\frac{w_j \tilde{\tau}_{jig}}{A_{jg}}\big) \Big)^{\frac{1}{1-\sigma_3}} \\ P_{ia}(\varphi) = \Big( \gamma_g u_i(\varphi)^{\epsilon_g - 1} P_{ig}^{1-\sigma_2} + \gamma_e u_i(\varphi)^{\epsilon_e - 1} P_{ie}(\varphi)^{1-\sigma_2} \Big)^{\frac{1}{1-\sigma_2}} \end{cases}$$

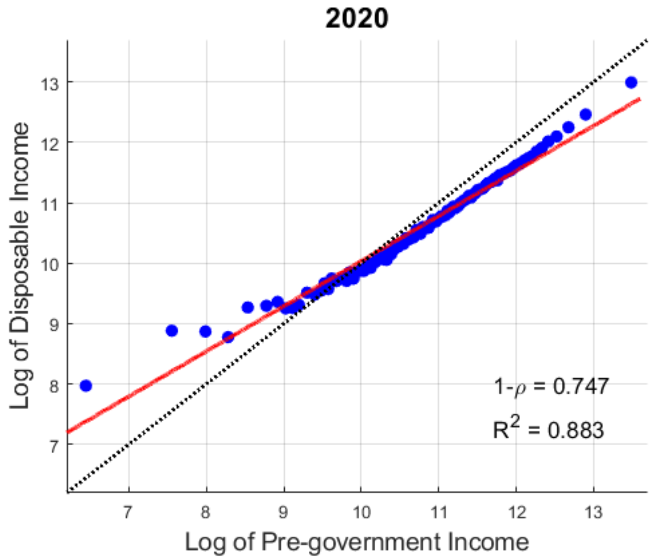
$$(xxvi)\;\; P_i(\varphi) = \Big( \sum_{k=a,m,s} \gamma_k u_i(\varphi)^{\epsilon_k - 1} P_k(\varphi)^{1-\sigma_1} \Big)^{\frac{1}{1-\sigma_1}}$$

$$(xxvii)\;\; X_{ie} = N_{ie} \int_{\phi} L_i \Big( \frac{\sigma_3}{\sigma_3 - 1} w_i^{1-\alpha} q_i^{\alpha} \Big)^{1-\sigma_3} \phi^{\sigma_3 - 1} s_i^*(\phi)^{\frac{\alpha(1-\sigma_3)}{\eta-1}} v(x_i^*(\phi)) dF_i(\phi)$$

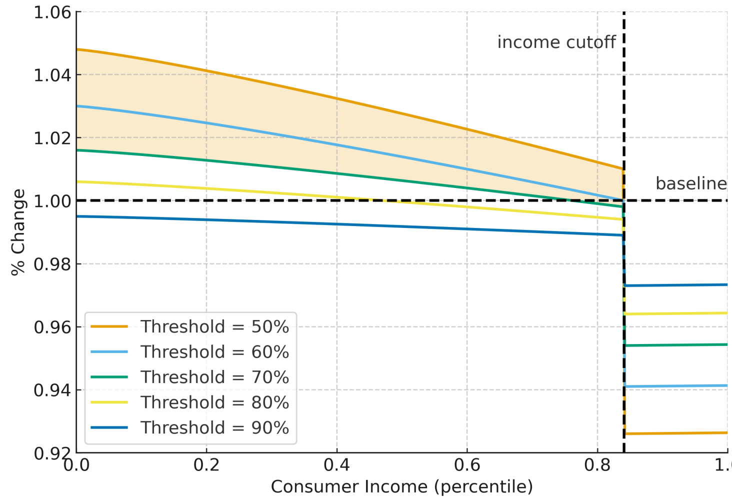
$$(xxviii) \begin{cases} X_{ijm} = L_j \int_{\varphi} \left( \dfrac{w_i \tau_{ijm}}{A_{im}} \right)^{1-\sigma_2} {P_{jm}}^{\sigma_2 - \sigma_1} P_j(\varphi)^{\sigma_1} u_j(\varphi)^{\epsilon_m} dH_j(\varphi), \forall i, j \\ X_{ijg} = L_j \int_{\varphi} \left( \dfrac{w_i \tau_{ijg}}{A_{ig}} \right)^{1-\sigma_3} P_{jg}^{\sigma_3 - \sigma_2} P_{ja}(\varphi)^{\sigma_2 - \sigma_1} P_j(\varphi)^{\sigma_1} u_j(\varphi)^{\epsilon_g + \epsilon_a - 1} dH_j(\varphi), \forall i, j \\ X_{ijs} = \begin{cases} L_j \int_{\varphi} \gamma_k \left( \dfrac{w_i}{A_{is}} \right)^{1-\sigma_1} P_i(\varphi)^{\sigma_1} u(\varphi)^{\epsilon_s} dH_j(\varphi), & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases} \end{cases}$$

$$(xxix)\;\; w_i L_i = \sum_j \big( X_{ijm} + X_{ijs} + X_{ijg} + X_{ije} + X_{ijb} \big) - dd_i$$

# Appendix D Calibration

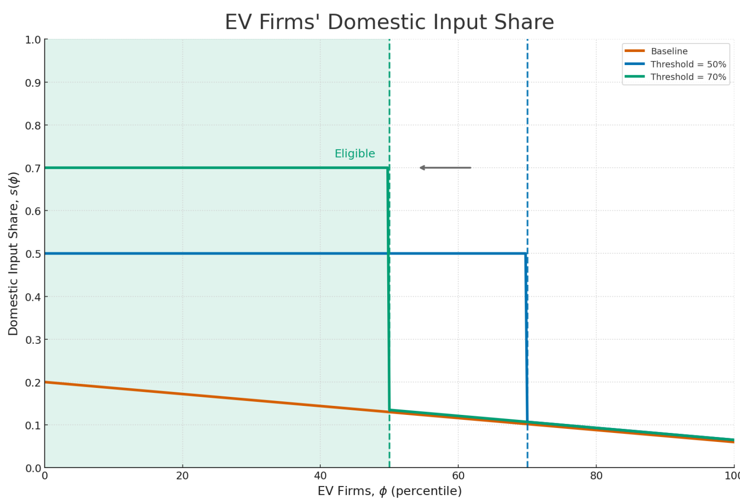


# Appendix E  Results




*Notes:* This figure illustrates the percentage change in electric vehicle (EV) purchases across consumer income levels and domestic content thresholds. The shaded area highlights the increase in EV adoption among eligible consumers—those below the income cutoff—between the 50% and 70% threshold levels. However, beyond the 70% threshold, their purchases begin to decline. In contrast, ineligible consumers—those above the income cutoff—exhibit a consistent reduction in purchases across all thresholds, though the magnitude of decline diminishes as the threshold becomes more stringent.

Figure E3: Percentage Change in EV Purchases Across Income Levels and Domestic Content Thresholds




*Notes:* This figure illustrates how EV firms adjust their battery sourcing decisions as the domestic content threshold rises from 50% to 70%. As the requirement becomes more stringent, less productive firms tend to comply earlier, while more productive firms are the first to deviate.

Figure E4: EV Firm decisions on Domestic Sourcing of Batteries Across Thresholds